Annals of the University of Craiova, Mathematics and Computer Science Series
Volume 42(1), 2015, Pages 3–12
ISSN: 1223-6934

Non-domination sorting genetic algorithm II for optimization of Priestley-Taylor transpiration parameters

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Abstract. Optimization of Two Source Energy Model (TSEB) parameters according to different local environmental characteristics is more important to well predict surface turbulent fluxes. To achieve such a target, multi-objective optimization methodology is a good approach inasmuch as several types of objective are minimized or maximized simultaneously. In this paper, this technique is implemented on a closed TSEB Model (Norman et al. 1995, Kustas et al. 1999). The main outputs of this model are the latent and sensible heats which are forming with Soil heat the total net radiation to surface. TSEB Model adaptation to semi-arid area was applying to enhance its performance. The Pareto optimization goal is to minimize latent and sensible heats Error while maximizing TSEB Model performance. Two transpiration parameters are selected as design variables (α_p and fg). Decision parameters are optimized using an evolutionary genetic algorithm, called NSGA-2. During summer 2003, the NSGA-2 gives a best Pareto optimum values for (α_p=0.99) and (fg=0.51). Thus, the results obtained here show the faithfully support of NSGA-2 through the calibration and optimization processes.

Key words and phrases. Non-Domination Sorting Genetic algorithm, Multi-Objective Optimization Problems, Objectif function, TSEB Model.

1. Introduction

Many standard parameters values using in TSEB Model published in literature are generally for wet region. But our experimental site is a semi arid then we should search some adapted values according to local environmental characteristics using calibration techniques. Classical methods for optimization are used in literature such as a simple gradient or steepest descent method. However, numerical methods for optimization suffer from some limitations such as the difficulty to escape from local minima and the dependence of the solution on the initial value chosen. But, Genetic Algorithm methods (GA) suggest an easy way to solve optimization problems based on genetic evolution of species mentioned by Darwin's theory. GA is much more applicable due to its ability to search through the work space, though its large computational time. A multi-objective algorithm (Fig. 1) should be applied because optimization problem has two objective functions (i.e: latent and sensible heats errors). For the optimization problem parameters of Priestley-Taylor, and fraction of the Leaf Area Index that is green are selected as design parameters. The influence of these design parameters on the TSEB Model outputs is assessed by varying each parameter in a specific range and sampling the model outputs; thereby, a data sheet can be obtained. Once the materials and methods are described, Non-domination Sorting Genetic Algorithm will be used for optimization. Afterwards, results will be showed with conclusion and perspectives.

This paper has been presented at Congrès MOCASIM, Marrakech, 19-22 November 2014.

2. Site area and data collection

2.1. Site description. The study site was located in the 275 hectare Agdal olive (Olea europaea L.) orchard in the southern side of Marrakech City, Morocco (31.601 N; 07.974 W). It is characterized by low and irregular rainfall (annual average of about 240 mm, but 263.4 mm has been collected in 2003). The climate is typically Mediterranean semi arid; precipitation falls mainly during winter and spring, from November to April. The atmosphere is very dry with an average humidity of 56 % and the evaporative demand is very high (1600mm per year), greatly exceeding the annual rainfall. The orchard was periodically surface irrigated through level basin flood irrigation, with water supplies of about 100 mm every each irrigation event. We have approximately 3 irrigation events during summer 2003. Each tree was occupied over 45 m2, and bordered by small earthen levy (about 30 cm) retained irrigation water (Williams et al, 2004). Plant spacing was about (6.5x6.5 m); the trees had an average leaf area index (LAI) of 3. Mean tree height was 6 m and ground cover was 55 % (Ezzahar, 2007).

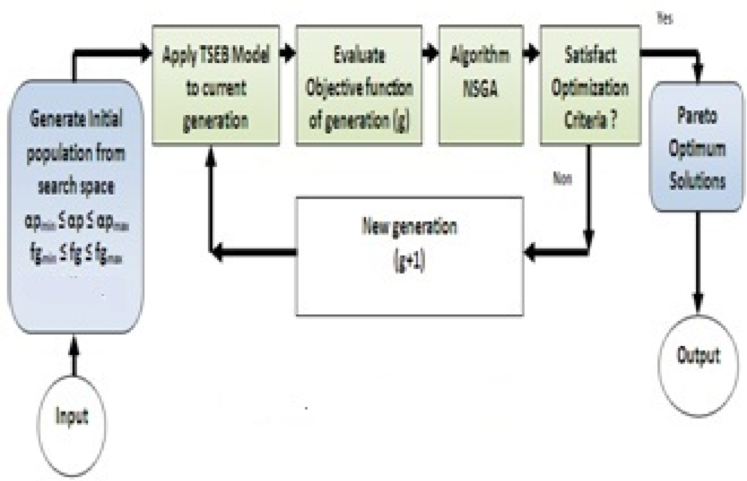


FIGURE 1. Iterative process of optimization model.

2.2. Measurements. Measurements were acquired at a sampling frequency of 20 Hz and passed through a low-pass filter to compute 30-min flux averages. Intensive data were collected in Agdal site. Vertical fluxes of heat and water vapor at 9.2 m height were registered on twelve month of 2003 and are measured by an Eddy-Covariance (EC) system (Ezzahar et al, 2007). Finally, the resulting dataset of sensible and latent heat fluxes were available for the 2003 growing seasons, with missing data for few days due to power supply troubles. Almost 6247 hourly observations, during daytime, everyday along the year 2003 without any exclusion related to season or climatic conditions, were used to run and evaluate TSEB model output. A 3D sonic anemometer (CSAT3, Campbell Scientific, Logan, UT) measured the fluctuations in the wind velocity components and temperature. An open-path infrared gas analyzer (LI7500, LiCor, Inc., Lincoln, NE) measured concentrations of water vapour. The wind speed and concentration measurements were made at 20 Hz on CR23X dataloggers (Campbell Scientific, Logan, UT) and on-site portable computers to enable the storage of large raw data files. Air temperature and humidity were measured at 8.8 and 3.7 m heights on the tower with Vaisala HMP45C probes. Total shortwave irradiance was measured at 9.25 m height with a BF2 Delta T radiometer. Net radiation was measured with a Kipp and Zonen CNR1 net radiometer placed over the olive canopy at 8 m height. Soil temperature was recorded at 5 cm depth at two locations approximately 30 m from the tower. Three heat flux plates continuously monitored changes in soil heat storage at the tower site. In addition, five point measurements of soil moisture variables were located throughout the site. Each point contained a pair of steel rods for time domain reflectometry (TDR) measurements at 40, 30, 20, 10 and 5 cm depths to estimate volumetric water content. Olive transpiration was measured by sap flow method following the procedure of Williams et al., 2003. Soil evaporation was computed as the difference between evapotranspiration measured by eddy correlation system and transpiration measured by sap flow method.

3. Brief description of TSEB Model

TSEB Model is based on energy balance closure using surface radiometric temperature, vegetation parameters and climatic data. TSEB outputs surface turbulent fluxes, and temperatures of canopy and soil. The version implemented in this study basically follows what is described in appendix A as the parallel resistance network. As such, the model implemented is described in detail in (Norman et al. 1995, Kustas et al. 1999).

4. Non domination sorting genetic algorithm 2 method

4.1. Overview. Non-domination Sorting Genetic Algorithm 2 (NSGA-2) is a Multi-Objective Evolutionary Algorithm (MOEA) for Multi-objective Optimization Problems (MOPs) using elite-preserving operators. This elitism is applied to make sure that a good solution found early in the run and will never be lost unless a better solution is discovered (K.A. De Jong, 1975). Moreover, the presence of elites enhances the probability of creating better offspring. Some EAs like Rudolph's MOEA, use only an elite-preservation strategy, but NSGA-2 (Deb et al 1999, 2000, 2002) also uses an explicit diversity-preserving mechanism. Afterwards, NSGA-2 classify individuals into several levels using a sorting process, based on non-dominance or Pareto optimal, elitist approach that preserves the diversity of peoples, safeguarding the best solutions found in previous generations on the one hand, and secondly, it apply to individuals a comparison operator based on a calculation of the distance of Crowding (Fig. 2).

4.2. Theoretical NSGA-2 bases. NSGA consists to optimize multi-objective functions in finding optimal values from a given search space containing normal reference values.

4.2.1. *Real coded solution.* The chromosome (individual) chosen to represent a solution is a vector coded of real floating number representing $\overrightarrow{X}$. The components of vector $\overrightarrow{X} = [x_1, x_2, \cdots, x_m]$ representing m parameters range from lower bound (a) to upper bound (b) of each parameter.

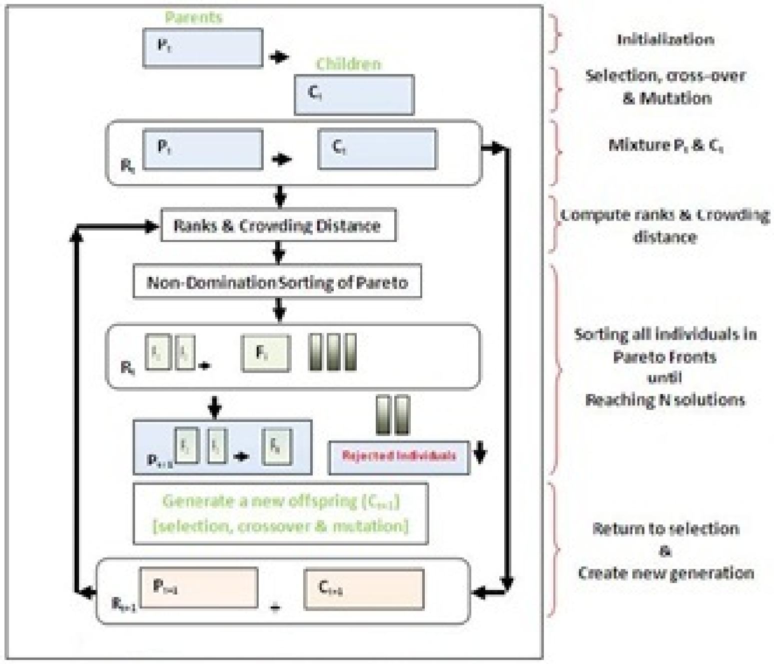


FIGURE 2. Iterative process of NSGA-2 (Deb et al. 2002).

4.2.2. *Multi-objective optimization problem.* The multi-objective optimization problem (MOP) consists to minimize or maximize simultaneously more than one objective function as follows:

$$min[\mathcal{J}(\overrightarrow{X})] = [f_1(\overrightarrow{X}), f_2(\overrightarrow{X}), \cdots, f_k(\overrightarrow{X})]$$

such that $\overrightarrow{X} \in \mathbb{R}^m$. The vector $\overrightarrow{X}$ have (m) unknowns components $[x_1, x_2, \cdots, x_m]$ in S which is the set of solutions. Usually, the target is to find design parameters like $\overrightarrow{X}$ that minimize (or maximize) k objectif functions forming the cost function $\mathcal{J}(\overrightarrow{X})$. If the objectif functions are in the trade-off relationship, it is difficult to optimize all objectif functions at the same time. In this case, the concept of dominancy and Pareto optimum solution should be utilized (Ringuest, J. L. 1992, Samadani et al. 2009).

4.2.3. *Principle of operations.* The various stages of operations of the algorithm NSGA-2 (Fig. 2) are:
- Creation of the first random population P_t of size N, from the search spaces, containing m decision variables based on the selected problem,
- Selection by tournament method based on preference rule and application of genetic operators crossover and mutation namely simulated binary crossover (SBX) and polynomial mutation (Deb et al. 2002). They are carried out with slight modifications from the original design to create a set of children's (offsprings) Q_t with crossover probability pc=0.9, and mutation probability pm=1/m,
- Mixture of individuals of two populations P_t and Q_t, to form a large population containing parents and children such as $R_t = Q_t$ U P_t,
- Calculation of all Pareto fronts F_i by sorting non-dominated solutions in Rt to form

P_{t+1}, furthermore we could use the Crowding distance to add other individuals until the size of P_{t+1} is equal to N,
- Return to Selection creating a set of children's Q_{t+1}, and so on until the termination criteria have been satisfied.

4.2.4. *Dominant solution definition.* Suppose $\overrightarrow{X_1}, \overrightarrow{X_2} \in \mathbb{R}^m$ are two solutions, when $(\forall i = 1, \cdots, k)$ as $f_i(\overrightarrow{X}_1) \leq f_i(\overrightarrow{X}_2)$ and $(\exists j = 1, \cdots, k)$ as $f_j(\overrightarrow{X}_1) \prec f_j(\overrightarrow{X}_2)$ then $\overrightarrow{X}_1$ dominates $\overrightarrow{X}_2$ and is a better solution. The concept of the Pareto optimum solutions is based on (k) objective functions, which are supposed to be minimized (Samadani et al. 2009). In this case, it is said that $\overrightarrow{X}_2$ is dominated by $\overrightarrow{X}_1$. Therefore, $\overrightarrow{X}_1$ is better than $\overrightarrow{X}_2$. On the other hand, the value of f_i in $\overrightarrow{X}_1$ is better than that of $\overrightarrow{X}_2$, but f_i for $\overrightarrow{X}_2$ is better than that of $\overrightarrow{X}_1$. Therefore, it is not possible to conclude which of two solutions is better. In this case $\overrightarrow{X}_1$ and $\overrightarrow{X}_2$ are called non-dominant solutions. In practice, multi objective optimization problems deal with non-dominant solutions. A set of these non-dominant solutions is called a Pareto optimum set. The line of the Pareto optimum solution is called a Pareto front.

4.3. Implementation of NSGA-2 to TSEB model. In all experiments, NSGA-2 experimental parameters are as follows: the population size is 20, the crossover rate is 0.9, the mutation rate is $\frac{1}{2}$ and we generate population until the 50th generation. The observations used in TSEB Model are taken each 30 minutes. The range of variation of the design parameters is taken from 0.5 to 2 for α_p and from 0.1 to 1 for fg. In this optimization we want to minimize the cost function, then we proceed the minimization to find a vector $\overrightarrow{X}_{opt}$ as follows:

$$\mathcal{J}(\overrightarrow{X}_{opt}) = inf[\mathcal{J}(\overrightarrow{X})]$$

where $\overrightarrow{X}_{opt} = [\alpha_p, fg]$ is the vector of parameters to be controlled, and $\mathcal{J}(\overrightarrow{X})$ is the cost function. The $[\alpha_p$ and fg are two transpiration parameters are selected as design variables. The state variable is the simulated latent heat $LE_{sim}(t, \overrightarrow{X})$ and sensible heat $H_{sim}(t, \overrightarrow{X})$ evolving in the time during summer 2003 between DOY=152 to DOY=243. The cost function is computed by comparing simulated latent and sensible heat $[LE_{sim}$, $H_{sim}]$ and observed latent and sensible heat $[LE_{obs}(t)$, $H_{obs}(t)]$ during the all period T. This two unknown parameters used in TSEB Model are estimated by optimization of the cost function with NSGA-2. The cost function to minimize are represented by a practical evaluation of $\mathcal{J}(\overrightarrow{X})$ where $\mathcal{J}(\overrightarrow{X}) = [f_1(\overrightarrow{X}), f_2(\overrightarrow{X})]$ as

$$f_1(\overrightarrow{X}) = \frac{1}{2}\int_0^T [LE_{sim}(t, \overrightarrow{X}) - LE_{obs}(t)]^2 f_2(\overrightarrow{X}) = \frac{1}{2}\int_0^T [H_{sim}(t, \overrightarrow{X}) - H_{obs}(t)]^2$$

where T is the time period, $f_1(\overrightarrow{X})$ is the latent heat Root Mean Square Error and $f_2(\overrightarrow{X})$ is the sensible heat Root Mean Square Error.

5. Results

Figure 3 shows the space of solutions (Pareto Front) representing all not dominated solutions obtained after 50 generations with 20 individuals' population. The Pareto-optimal Front is also shown in the figure which demonstrates the abilities of NSGA-2 in converging to the true front and in finding diverse solutions in the front. This problem has a non-convex Pareto-optimal front. The NSGA-2 converged and distributed uniformly on each part of the Pareto-optimal front. Figure 4 gives a clear image about the behaviour of NSGA-2 algorithm. It shows also that the convergence process moves to lower values of surface fluxes Errors, through generations then confirm a real effect of elitist approach to preserve elite individuals in multi-objective optimization problem. The choice of two objective functions let NSGA-2 algorithm to find a compromise between both them, then it preserve in long time choice of elite solution respecting a both lower of cost functions (Table 1). In Figure 5 Diagrams of the founded Pareto solutions for our two design parameters α_p and fg is shown. All these plotted solutions are those that dominate other derived solutions during searching through the objective space. Every single point in these diagrams introduces an optimized set of $\overrightarrow{X}_{opt} = [\alpha_p, fg]$ that is in accordance with a specific set of design parameters. In order to determine a single set of optimized design parameters for the surface fluxes error, one should suggest a specific constraint. In other words, a logical constraint like the relation between objectives' quantity should be considered and imposed on the achieved Pareto solutions. Hence, just the Pareto solution that satisfies the constraint would be the final answer. The constraint which we consider in this paper is the compromise between both latent and sensible heat Error to may be compensate any effects on evapotranspiration quantity. Hence, the solution that have lower value of both errors in comparison with others are selected, which have 0.90 to α_p and 0.68 to fg. In general, the problem of multi-objective optimization has to reduce to the single objective problem which is the global cost function to minimize are represented by a practical evaluation of $\mathcal{J}(\overrightarrow{X})$ where $\mathcal{J}(\overrightarrow{X}) = [f_1(\overrightarrow{X}), f_2(\overrightarrow{X})]$, otherwise the achieved Pareto solutions can not be applied for a specific application. The final set of Pareto optimum solutions is applied to TSEB Model, then Figures 6 and 7 show the comparison of measured and predicted daily surface fluxes heats before and after optimization process. These figures show an improvement of latent and sensible heat representativeness. Furthermore, the Errors decrease for latent heat from $251 W.m^2$ to $67 W.m^2$, and for sensible heat from $220 W.m^2$ to $68 W.m^2$. Furthermore the measured and predicted surface heats evolve both in the same direction expect during irrigation event, because some physical conditions are occurred due to submerged soil by traditional irrigation system water. The estimation of Priestley-Taylor formulation has been improved since the TSEB Model performance will come acceptable with best parameters giving by 50 generations with 20 individuals' population using NSGA-2 algorithm.

Table 1. Main Elites through 3 Tests of design parameters and objectif functions by NSGA-2.

Test Num	Population size	Generation Num	Occurence	α_p	fg	$f_1(\overrightarrow{X})(W.m^{-2})$	$f_2(\overrightarrow{X})(W.m^{-2})$
1	25	50	29	0.96	0.64	75	75
2	50	50	36	0.81	0.76	75	75
3	25	100	79	0.99	0.51	66	83

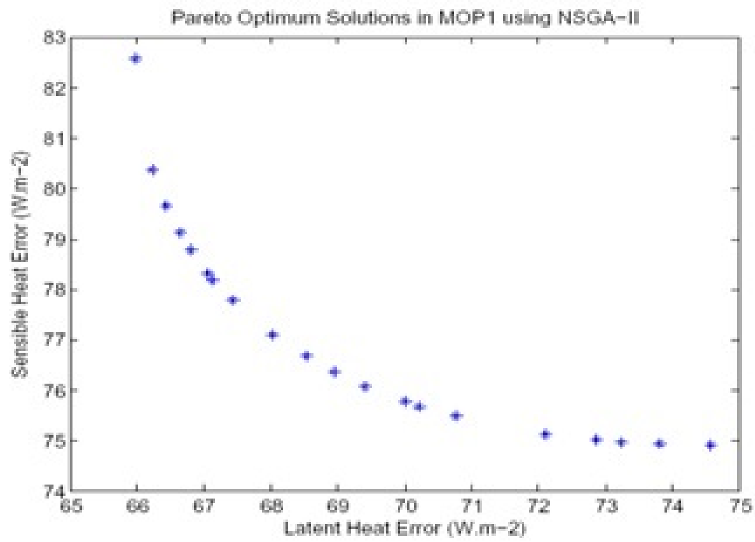


FIGURE 3. Pareto optimum solutions optimized through 100 generations and 25 individuals population.

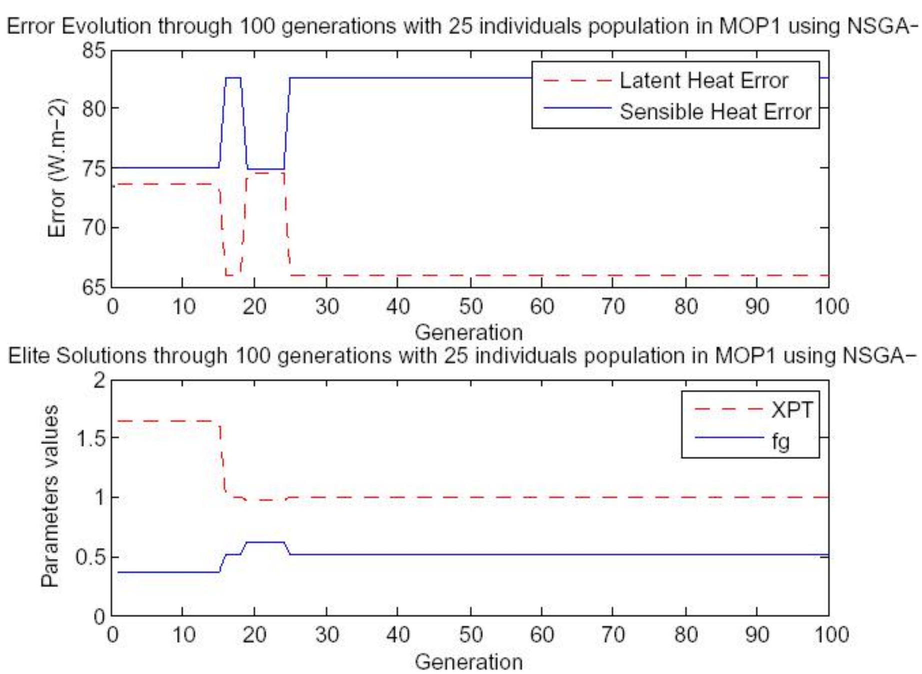
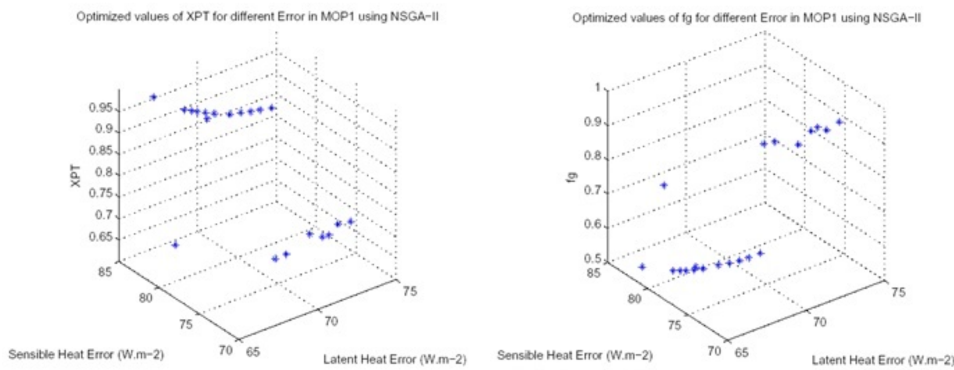
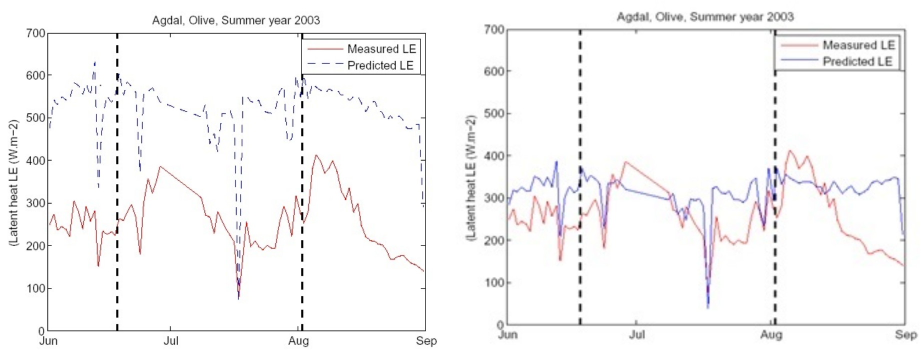


FIGURE 4. Error evolution & Elite solutions through 100 generations and 25 individual's population.



(a) (b)

FIGURE 5. Pareto optimum solutions space for (α_p) founded through 100 generations with 25 individuals population (a), Pareto optimum solutions space for (fg) founded through 100 generations with 25 individuals population (b)

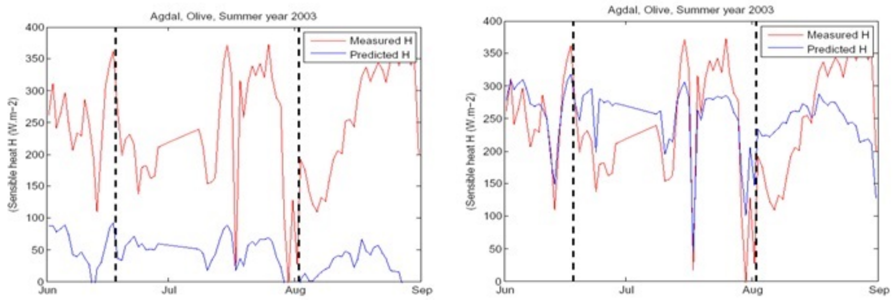


(a) (b)

FIGURE 6. Comparison between predicted and measured latent heat before optimization with Standard values of $\overrightarrow{X}_{opt} = [(\alpha_p) = 1.26, fg = 1]$ (a), Comparison between predicted and measured latent heat after optimization with Standard values of $\overrightarrow{X}_{opt} = [(\alpha_p) = 0.99, fg = 0.51])$ from 50 generations. (b)

6. Conclusion

In this study we conclude that a good derivation of the Pareto optimum solutions by NSGA-2 requires a large number of calculation iterations. NSGA-2 is fast than a simple standard Genetic Algorithm and becomes better with elitist multi-objective algorithm. As the main result of this work, are resolving Multi-objective Optimization Problem and the pre-calibration of the TSEB Model to enhance performance which plays an important role in adjusting surface fluxes quantities. The results obtained don't change significantly from several attempts, so the final optimal vector respecting both lower latent and sensible heat errors constraint is $\overrightarrow{X}_{opt} = [\alpha_p = 0.90, fg = 0.68]$.



(a) (b)

FIGURE 7. Comparison between predicted and measured sensible heat before optimization with Standard values of $\overrightarrow{X}_{opt} = [(\alpha_p) = 1.26, fg = 1]$ (a), Comparison between predicted and measured sensible heat after optimization with Standard values of $\overrightarrow{X}_{opt} = [(\alpha_p) = 0.99, fg = 0.51]$) from 50 generations. (b)

The results show an improvement of canopy transpiration then also enhance the TSEB Model performance, since Root Mean Square Error becomes 67 $W.m^2$ and 68 $W.m^2$ respectively for latent and sensible heat. Thus, the results obtained in this study show the fast suitable support of Evolutionary Algorithm in the calibration and optimization problem. We conclude also that Evolutionary Algorithms optimization could replace a long effort in time and budget since it improve TSEB Model results through using a suitable fitness function and genetic operators.

Acknowledgment

This work is considered within the framework of research between the University of Cadi Ayad Gueliz, Marrakech, Morocco, and the Department of National Service of Meteorology, Morocco (DMN, Morocco). The first author is very grateful for encouragement to all his family especially to Mrs F. Bent Ahmed his mother, Mrs K. Aglou his wife and Mr Mahjoub Mouida his brother and his sister Khadija Mouida. Finally the authors gratefully acknowledge evaluation and judgments by reviewers, and the editor.

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