CROP PRODUCTION AND WATER PRODUCTIVITY SIMULTANEOUSLY OPTIMIZATION OF SOYBEAN PLANT USING TWO META-HEURISTIC ALGORITHMS

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ABSTRACT

The maximum crop production achievement in arid and semi-arid regions is the main issue that requires the optimum use of different variables of crop and water. Therefore, this research has been carried out for simultaneous optimization of water productivity (WP) and for high crop productivity under deficit irrigation management conditions. An original data series has been used for this research from an experimental design that was conducted in the form of randomized complete blocks design with three replications and seven irrigation treatments of different growth stages during two conductive crop seasons 2010 and 2011. The genetic algorithm has been applied as a multi-objective (MOGA) and under two scenarios of the priority of objective functions. Also, in order to investigate the application of the simulated annealing algorithm (SA), in a combined optimizing of two objective functions of soybean WP and plant production using weight summation method, it has been converted to a single objective one. The results have shown that under the first scenario conditions, the optimum grain yield and optimum WP are 3,827 and 3,953 kg ha^{-1} and 0.53 and 0.58 kg m^{-3} ha^{-1} in 2010 and 2011, respectively. The results in the combined optimization under the second scenario conditions show the amounts of optimum crop production and WP are 3,838.1 and 3,902.7 kg ha^{-1} and 1.12 and 0.75 kg m^{-3} ha^{-1} in the two seasons, respectively. Comparison of the MOGA and SA results has indicated that MOGA has a better capability in simultaneous optimization of the two objective functions. Maximum crop production was 4446 kg ha^{-1} for consuming 664.9 mm irrigation water. Also, the maximum WP was 0.82 kg m^{-3} ha^{-1} for consuming 375.8 mm irrigation water. Therefore, the dual-objective genetic optimization method can well optimize both objective functions and achieve the desired results in optimal grain yield and WP under constrained water resources.

Keywords: grain yield, Multi Objective Genetic Algorithm (MOGA), Simulated Annealing (SA), soybean, water productivity.

INTRODUCTION

In the recent decade, water resources are becoming scarcer due to climate change and pollutions (Kloss et al., 2012). This is especially the case in arid and semi-arid regions where irrigated agriculture is the largest contributor to water use and at the same time is the main source for food. Therefore, the Food and Agriculture Organization of the United Nations (FAO) called for a revolution in water management and water use efficiency (Kloss et al., 2012). In Iran, the shortage of water resources is one of the most important restricting factors in the agriculture sector. On the other hand, low water productivity (WP) in agriculture leads to losing large amounts of available water resources (Sepaskhah et al., 2007). Farmers try to increase their crop production by using water more than their crop water requirement while there is optimum irrigation that can cause an increase in WP and crop yield simultaneously (Kassam et al., 2007; Abbasi and Sepaskhah, 2011). Usually, there are two contradictory objectives in this problem. The first objective which is to increase crop yield, water consumption must be increased so that the crop yield based on crop production function increases. On the other hand, according to WP equation, water consumption must be decreased so that improving WP

Received 17 August 2021; accepted 1 March 2022.

(Pally and Zell, 2009).

Different types of optimization methods have been developed to solve the water optimization problem, especially in natural resources. Some of these methods have patterned the kind of optimization in the actual world such as Genetic Algorithm (GA), Ant Colony Optimization (ACO) algorithm, Honey-Bees Mating Optimization (HBMO) algorithm, Particle Swarm Optimization (PSO) algorithm, etc. The select of optimization method depends on the type and number of objective functions. Multi-Objective Genetic Algorithm (MOGA) is the optimization method can use in multi-objective optimization problem (Ghodspour et al., 2021). The MOGA is used in many multi-objective problems. Inherent characteristics of MOGA including multi-direction and general search by saving optimal results from one generation to another, and controllability of various objective functions and constraints, make this algorithm suitable for optimization of multi-objective functions (Yapo et al., 2007; Pally and Zell, 2009; Babazadeh and Sarai-Tabrizi, 2013). Using MOGA is one of the most effective solutions of water optimization that have two or more contradictory objective functions which must be considered simultaneously. Among various kinds of meta-heuristics algorithms, multi-objective genetic algorithm (MOGA) is known as one of the most robust algorithms in optimization of multi-objective problems (Pally and Zell, 2009; Sundar et al., 2010). Optimal agricultural water allocation due to water constrains and plant production is the issues that use MOGA. One of indices that are used for evaluation of irrigation management is WP. The WP is crop production for each cubic meter of consumed water. Considering the crisis of water shortage in the world, nowadays tracing of WP index is very important (Tafteh and Sepaskhah, 2012; Sarai Tabrizi et al., 2013; Shirshahi et al., 2020). To achieve sustainable and successful agricultural production, available water and soil resources must be used to produce crops that in fact can bring about combined maximum WP and the maximum economical net benefit. The most important factor in agriculture crop pattern is economical net benefit and WP. Usually economical net benefit is gained in treatments that have maximum crop yield (Kijne et al., 2003; Geerts and Raes, 2009). Although on regions with high value of water, the maximum net benefit could be achieved less than maximum crop production.

Shirshahi et al. (2020) applied a two-level optimization model. The second-level objective was to maximize the profit and minimize the disruption of water resource sustainability in branch and distributary canals in the district of Qazvin, Iran. Based on the results of the first-level objective, the scenario of a 10% reduction in irrigation water increased economic productivity at various levels by an average of 25 USD per cubic meter of water while maintaining proper income. According to the considered objective functions, the amount of water consumed in optimal conditions reduced from 100 of water allocated to 80%.

The most important innovation in the present study is the use of SA which to the best of our knowledge, was not used in any studies in arid and semi-arid regions in order to optimize soybean WP and plant production by using the field data. The main objective of this research was to investigate and compare the performance of genetic algorithm (GA) and SA in multi-objective optimization.

MATERIAL AND METHODS

The field experiment was conducted in summer of 2010 and 2011 at the research field of University of Tehran in Karaj, Iran, at 51° North longitude and 36° East latitude at the altitude 1312 m above sea level (Figure 1). The data used in this research was obtained from a field experimental design; randomized complete blocks design with three replications on Sahar soybeans. The seven irrigation treatments including full irrigation (irrigation throughout growing stages without water stress) (WS0), deficit irrigation in vegetative growth stage (WS1), in flowering stage (WS2), in grain filling stage (WS3), in vegetative growth and flowering stage (WS4), in vegetative growth and grain filling stages (WS5) and in flowering and grain filling stages (WS6). For optimization of objective function, the MOGA toolbox in MATLAB software (MATLAB 8) has been used for combined optimization of soybean crop yield and WP.

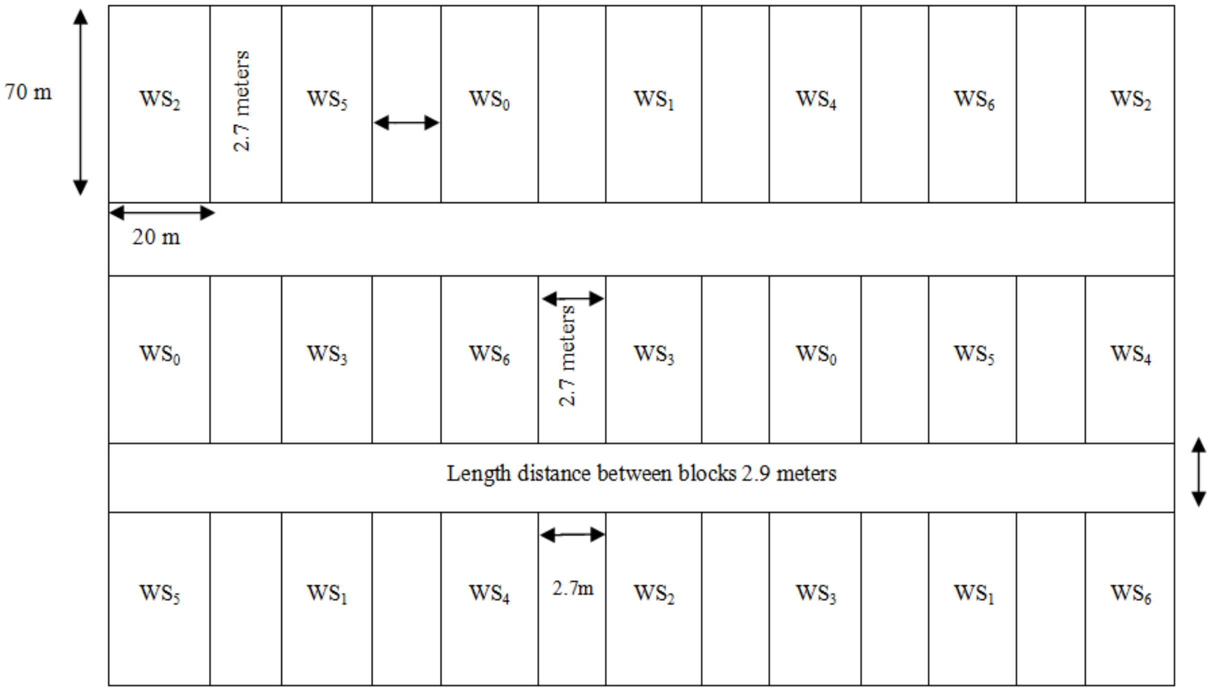

Figure 1. The schematic of the experiment blocks in the research field

The present study has two objectives function included to maximize crop yield and to maximize WP. In this problem, decision variable (X) is the amount of irrigation water. Since in each plant growth stage, the sensitivity of plant to water stress is different, the amount of irrigation water in each different water stress treatment and different growth stages must be considered. That is the response of different soybean growth stages to water stress that must be considered. FAO 33, publication has recommended equation 1 for estimating actual crop yield based on the amount of irrigation water (Doorenbos and Kassam, 1979; Bras and Cordova, 1981).

$$Y_i = 1 - K_y \times \frac{AET_i}{PET_i} \quad (1)$$

where, i is plant growth stages, Y_i is the amount of crop yield per plant growth stage, $K_y(i)$ is the crop response factor to water in the ith plant growth stage, AET_i is the summation of actual crop evapotranspiration during plant growth stages and PET_i is the summation of potential crop evapotranspiration during soybean plant growth stages. The amount of total crop yield is obtained by multiplying maximum crop yield by crop yield per plant growth stage that is given in equation 2 (Doorenbos and Kassam, 1979; Bras and Cordova, 1981).

$$Y(I) = Y_m \prod_i Y_i \quad (2)$$

where, $Y(I)$ is the amount of total crop yield at the end of the growth period, Y_m is the amount of maximum crop yield under optimum conditions and Y_i is the amount of crop yield per plant growth stage. Crop yield functions (crop production functions) (Y) are given in equations 3 and 4 and also WP equations based on the first objective function was defined as equations 5 and 6 for maximizing WP. WP objective functions are given in equation 5 and 6 (gotten from field studies).

$$Y_{2010} = -1 \times (-0.00003X^2 + 0.038X - 10.02) \quad (3)$$

$$Y_{2011} = -1 \times (-0.002X^2 + 16.45X - 65.7) \quad (4)$$

$$WP_{2010} = -1 \times (-0.229X^2 + 260.7X - 7.370) \quad (5)$$

$$WP_{2011} = -1 \times (-0.058X^2 + 0.09X - 2.13) \quad (6)$$

where, Y is crop yields in kg ha^{-1}, WP is water productivity kg.m^{-3} and X is irrigation water in mm. Table 1 shows field experimental data of actual and maximum yield, actual and potential evapotranspiration and crop response factor to water deficit. In Table 2, statistical comparison of WP and crop yield between two experimental years are presented and Table 3 shows the comparison of the means of soybean WP and yields under different water stress treatments.

Table 1. The amount of crop yield and crop response factor to water (K_y) in different water stress treatments

Irrigation treatments	Water stress stage	Y_a (kg/ha)		Y_m (kg/ha)		AET (mm)		PET (mm)		K_y	
		2010	2011	2010	2011	2010	2011	2010	2011	2010	2011
WS_1	V	4012	4096.4	4100	4313	552	564	650	665	0.142	0.339
WS_2	F	3260	3274			500	505.2			0.888	1.016
WS_3	FP	3590	3891.5			569	590			0.998	0.889
WS_4	V & F	3497	3508.9			523	526.5			0.753	0.892
WS_5	V & FP	3382	3497			487	495			0.698	0.755
WS_6	F & FP	2467	2498			369	413.7			1.019	1.122

Note: Y_a is the actual crop yield, Y_m is the maximum crop yield in control treatment, AET and PET are the actual and potential evapotranspiration; V: Vegetative; F: Flowering and FP: Filling Pod, respectively.

Table 2. Analysis of soybean crop yield and WP under water stress in 2010 and 2011

SOV	DF	Crop yield		WP	
		2010	2011	2010	2011
Replication	2	120137	145126	0.084	0.071
Water stress	6	1847626**	1967121**	0.164*	0.188*
Error	12	353671	282813	0.057	0.039
C.V.		14.3	11.7	16.9	13.4

** and * are significantly different at 1% and 5% levels, respectively.

Table 3. Comparison of means soybean crop yields and WP under water stress

Irrigation treatments	The number of irrigations	Irrigation water (mm)		Crop yield (kg/ha)		WP (kg/m^3/ha)	
		2010	2011	2010	2011	2010	2011
WS_0	8	589.52	665	4100^a	4313^a	0.436^c	0.649^b
WS_1	6	489.52	521	4012^a	4096.4^{ab}	0.532^a	0.786^a
WS_2	6	471.32	497	3260^c	3274^c	0.48^b	0.659^{ab}
WS_3	5	435.5	519.9	3590^b	3891.5^b	0.49^b	0.748^a
WS_4	4	410	496.8	3497^b	3508.9^{bc}	0.501^{ab}	0.621^b
WS_5	3	367.2	458.7	3382^{bc}	3497^{cb}	0.51^a	0.681^b
WS_6	3	361.5	375	2467^d	2498^d	0.518^a	0.53^c

Based on Duncan's Multiple Range Test, treatments shown with the same letter are not significantly different.

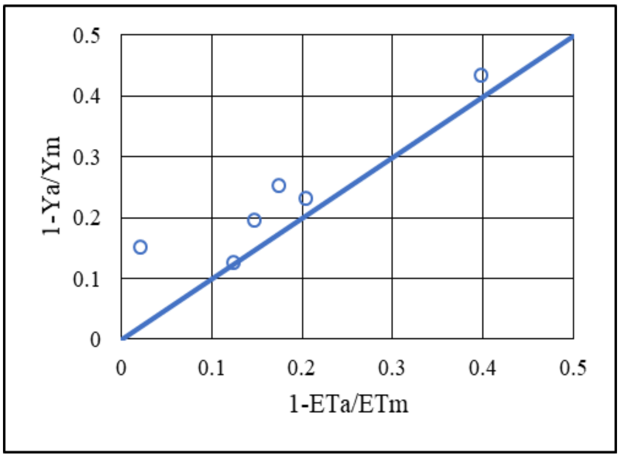

Figure 2a. Regression trend of soybean crop yield reduction factor (for the whole the growing season) in 2010

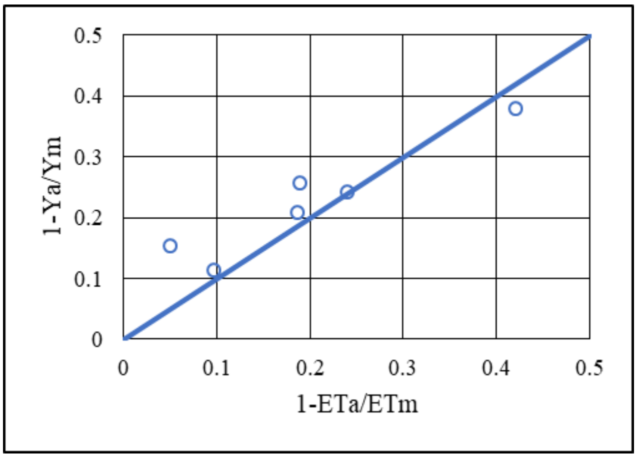

Figure 2b. Regression trend of soybean crop yield reduction factor (for the whole the growing season) in 2011

Figure 3 shows the flow chart of the MOGA optimization analysis. In this optimization process, at first, the population is initialized within the specified variable ranges. After evaluation of this population, based on non-dominated sorting approach, the generated alternatives are classified into different fronts. The population members are ranked according to their fitness values (frank) and are selected for genetic operation, on a pair-wise comparison to produce an offspring in the generation. In this selection process, if any pair is having the same rank, then the crowded distance values (fdist) calculated using crowding distance assignment operator (Deb et al., 2002). To change the attributes of the offspring, crossover and mutation operations were performed. The procedure is repeated for a pre-specified number of generations, with the goal of achieving diverse set of non-dominated solutions, possibly attaining true Pareto optimal solutions. To preserve the best solutions obtained through generations and to speed up the convergence, the algorithm uses elitism, in which the combination of parents and offspring population are grouped into different fronts and the best individuals selected for the next generation. Figure 3 shows the flowchart of Multi-objective Genetic Algorithm. In this study chromosomes are coded by real values. To handle the constraints in MOGA, the natural self-adaptation mechanism of the evolutionary algorithms is useful to bias the search through a constrained space. For this purpose, three criteria are used to select the best individuals from a generation (Deb et al., 2002). (I) Out of two feasible solutions, the one with better fitness value is preferred. (II) If one solution is feasible and the other one is infeasible, the feasible one is preferred. (III) If both solutions are infeasible, the one with the lowest sum of constraint violations is preferred (Reddy and Kumar, 2006) (Figure 3).

Simulated Annealing (SA) algorithm

The principle of SA algorithm is the correction of repeated simulation of rearrangement of molecules in a liquid that is cooling. The energy of the molecules is equal to the cost function that is optimized by this repeated correction algorithm (Grafton et al., 2018; Sears et al., 2018). Thus the objective of SA algorithm is to obtain a close result of absolute optimum with slow convergence toward the final result. SA algorithm flowchart is shown below (Figure 4).

In order to investigate the application of SA algorithm at simultaneous optimization of two objective functions of crop production and water productivity, the two objective functions problem has been converted to the single objective problem by using weighted sum method. Then by changing the allocated weights to two objective functions, the results of Pareto front were obtained. The properties of used SA algorithm in this study are shown in Table 4.

Table 4. The Parameters and the characteristics of MOGA of the study

Production function	Constrained dependent function
Size of initial population	35
Fitting scale	Ranking
Choice function	Stochastic uniform function
Mutation function	Gaussian
Mutation probability	0.35
Amount of penalty index	125
Stop criteria	2000 iteration or $1*10^{-12}$ tolerance between 2 consecutive results
Number of decision variables	One
Decision variables	Irrigation water
Number of objective functions	2
Chromosome length	50
Crossover probability	0.8
Constraints	Lower Bound = [361.5] or WS_6 2010
	Upper Bounds = [665] or WS_0 2010

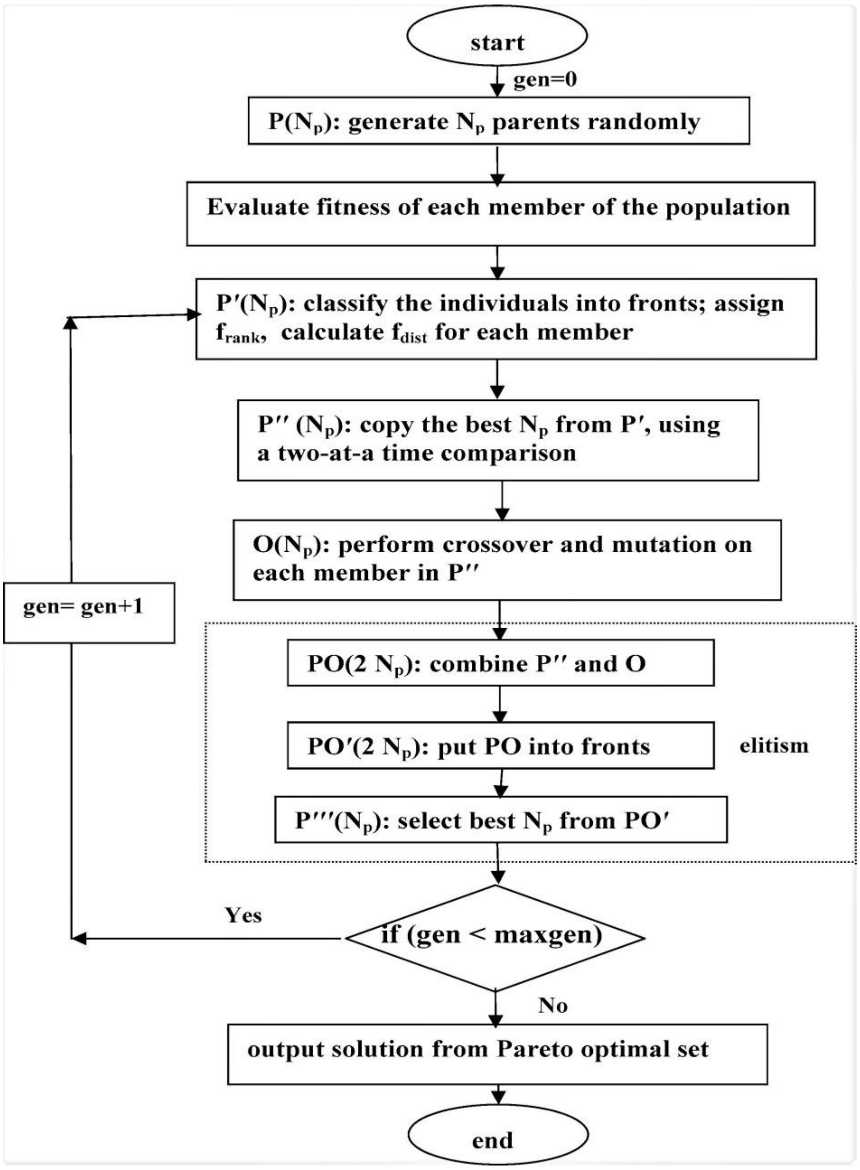

Figure 3. Flowchart of Multi-objective Genetic Algorithm (MOGA)

The weighted sum method

One of the most general methods for multi-objective optimization is the weighted sum method shown in equation 7.

$$U = \sum_{i=1}^{n} \omega_i F_i(X), \ \sum_{i=1}^{n} \omega_i = 1, \ \omega_i > 0, \ i = 1, \ldots, n \quad (7)$$

where, U is objective function, ω is the weight and $F(X)$ is function. If all weights in equation 7 are positive, the minimum value of equation 7 is the same as the optimum Pareto (Zadeh, 1963). Numerous researchers have developed systematic methods for choosing weights (Eckenrode, 1965; Hobbs, 1980; Hwang and Yoon, 1981; Voogd, 1983). In this research, ranking method for choosing weights (Yoon and Hwang, 1995) has been selected, in which the different objective functions are arranged based on the degree of importance. The lowest important objective function receives weight one and corrected weights with continual increase of the objective functions receive higher importance degrees. In this research, considering equation 3 to equation 6, the objective functions were written in the form of equation 8 and equation 9.

$$U_{2010} = \sum (\omega_1 Y_{2010} + \omega_2 WP_{2010}) \quad (8)$$

$$U_{2011} = \sum (\omega_1 Y_{2011} + \omega_2 WP_{2011}) \quad (9)$$

where, U_{2010} and U_{2011} is objective function in two years, ω is the weights coefficient, Y and WP are Yield and Water Productivity, respectively.

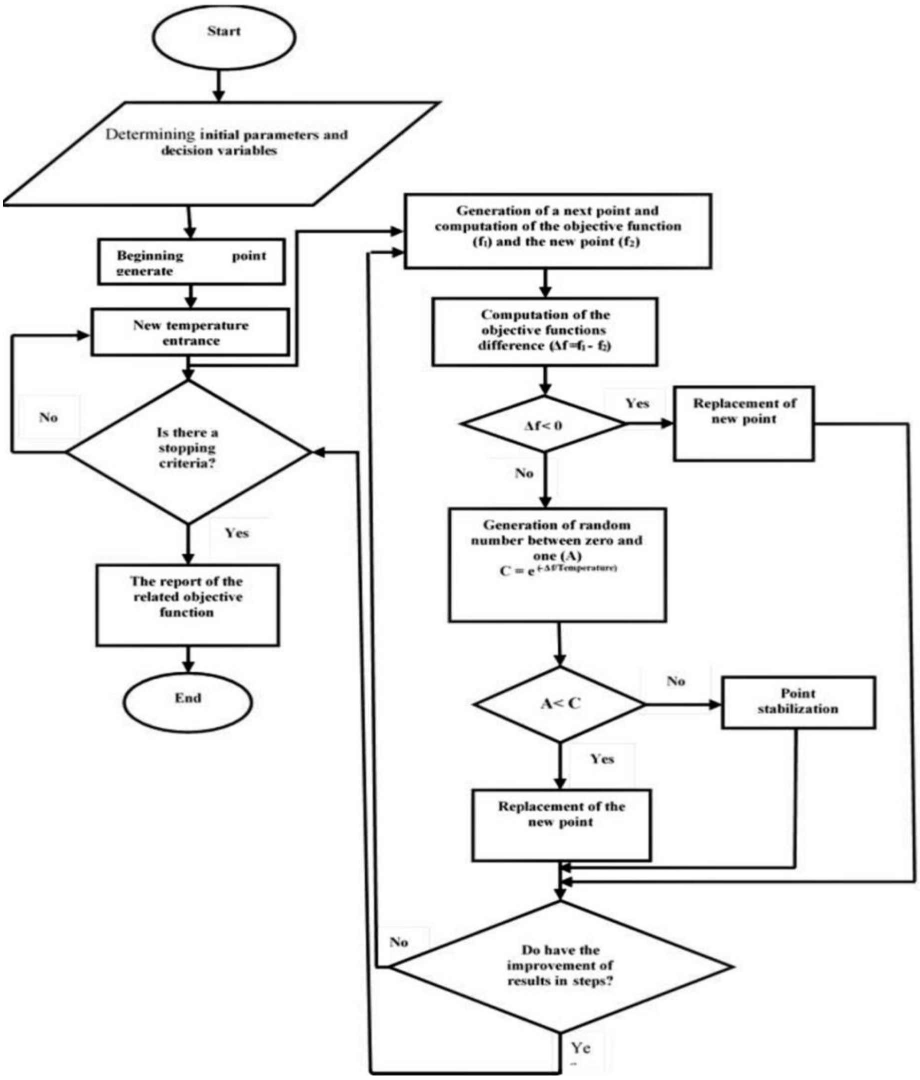

Figure 4. The flowchart of Simulated Annealing (SA) algorithm

RESULTS AND DISCUSSION

Combining of optimizing Water Productivity (WP) and crop production

The main problem that in dealing with multi-objective optimization is that unlike GA problem in which there is one result, in MOGA, there are a number of results that each can be optimized from a special point of view. This set of results in MOGA is called Pareto front. In fact, in Pareto front scatter curve, each expresses a series of results that considering its importance is regarded as an optimum result (Konak et al., 2006). Figure 5 shows the average variation trend between objective functions in consecutive generations. Considering the Figure 5, in consecutive generations, the average difference between objective functions decreased which showed the convergence of results toward optimum results. Ranges of average variation of differences between the results of objective functions in the Figure 5 are between 10 and 50 days. Fewer differences show that initial rates of model default have been chosen reasonably. In fact, the efficient result is a point that there aren't any better-neighboring points in the search area in this condition and space. This is the optimum point for both chosen objective functions as an absolute optimum point that has introduced by MOGA. The concept of efficient result leads to defining effective results instead of one point, it is extended to a set of points in the search space. That is the efficient result front is a set of the result points that none prevails others and among the collection of the results, is the front that presents the best optimum results in the search space. Efficient results front is called relative Pareto. The Pareto front curve in the first scenario is in the form of Figure 6.

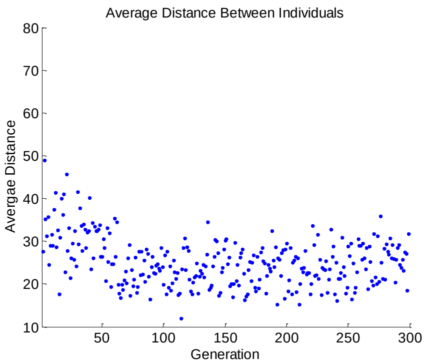

Figure 5a. Variation trend of average difference between the results of objective functions in consecutive generations in the first scenario in 2010

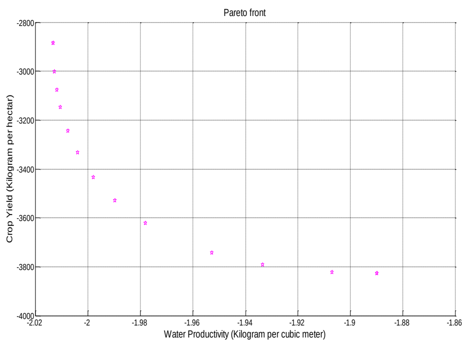

Figure 5b. Variations trend of Pareto front in optimization of objective functions in the first scenario in 2010

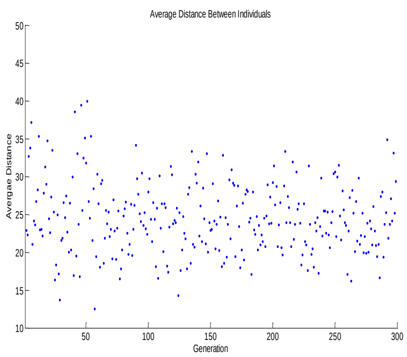

Figure 5c. Variation trend of average difference between the results of objective functions in consecutive generations in the second scenario in 2010

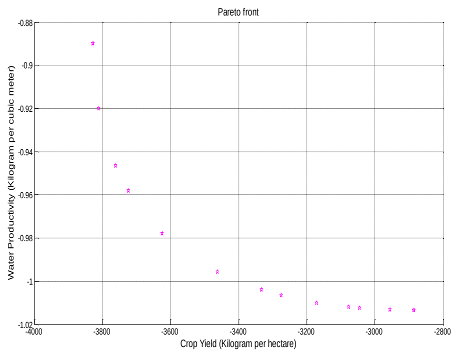

Figure 5d. Variations trend of Pareto front in optimization of objective functions in the second scenario in 2010

Figure 5. Variation trend of Average differences and Pareto front in optimization of objective Functions in 2010

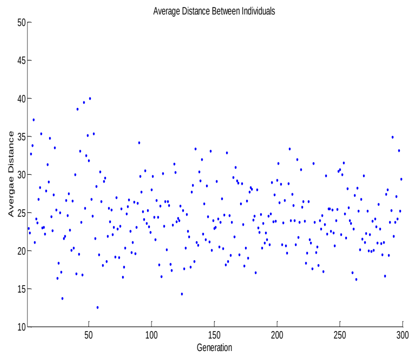

Figure 6a. Variation trend of average difference between the results of objective functions in consecutive generations in the first scenario in 2011

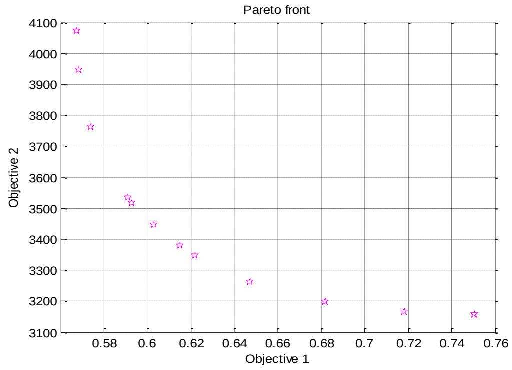

Figure 6b. Variations trend of Pareto front in optimization of objective functions in the first scenario in 2011

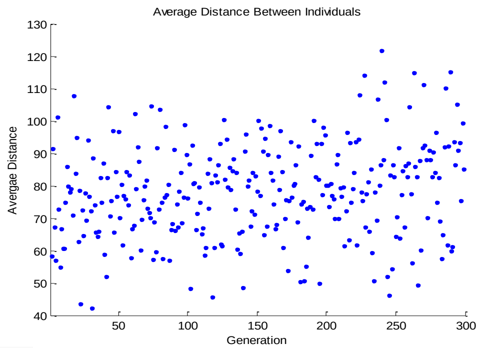

Figure 6c. Variation trend of average difference between the results of objective functions in consecutive generations in the second scenario in 2011

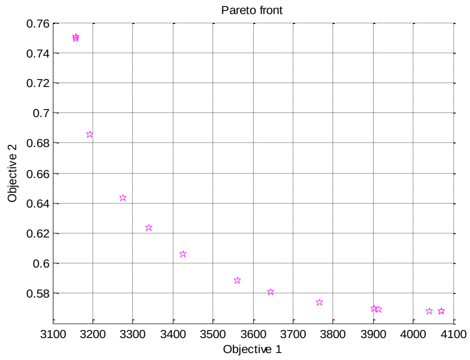

Figure 6d. Variations trend of Pareto front in optimization of objective functions in the second scenario in 2011

Figure 6. Variation trend of Average differences and Pareto front in optimization of objective Functions in 2011

In the multi-objective optimization, objectives could be optimized simultaneously two by two. It must be mentioned, that between the two objectives the one that is more important should be put on the vertical axis and the second important one on the horizontal axis. This situation is usually called the first scenario, and this is the MOGA default and if the positions of the functions are reversed (the first important objective function on X-axis and the second important objective function on the Y-axis). The pattern is called the second scenario. In most cases of researches, these two scenarios produce completely different results. In the first scenario of this study, the results if this combined optimization show that the optimum amounts of WP change between 0.497 and 0.538 kilograms per cubic meter in hectare and the optimum amounts of crop yield on vertical axis also change from 2800 to 4000 kilograms per hectare. The optimum amounts of objective functions in the last seven consecutive replications of MOGA to reach optimum amounts of objective functions are given in Table 5. According to the artificial intelligence science, MOGA uses two processes of elitism and quick convergence assuming initial suitable randomized number to reach optimum amounts of objective functions and satisfies at least one of stop criteria (Table 5).

Table 5. The optimum amounts of irrigation water and objective functions in the first scenario

Replication No.	The Optimum Irrigation Water (mm)		The Optimum Crop Yield (kg/hec)		The Optimum WP (kg/m^3)	
	2010	2011	2010	2011	2010	2011
1	599.09	554	3622.518	3561.75	0.506	0.58
2	633.33	548.66	3148.435	3375.14	0.497	0.54
3	629.23	631.5	3212.059	3497.63	0.501	0.59
4	569.21	574.47	3827.041	3907.12	0.529	0.53
5	588.43	610.65	3742.456	4072	0.512	0.57
6	626.46	628.81	3576.414	3891.9	0.520	0.61
7	573.78	603.26	3822.261	3953.43	0.524	0.58

According to Table 5, the best crop yield obtained in the 4th and 5th replications of optimization model from the last 7 consecutive replications is equal to 3827.041 and 4072 kg ha^{-1} in 2010 and 2011, respectively. Also, the second replication with crop yield of 3148.435 kg ha^{-1} has a minimum crop yield among the last 7 replications. On the other hand, replication numbers 4 and 7 have the most WP equal to 0.53 and 0.52 kg.m^{-3} ha^{-1} in 2010 and 2011, respectively. The results of this research showed that there is a direct relationship between optimum WP and optimum crop yield. The least amount of WP in replication number 2 was 0.50 kg m^{-3} ha^{-1}. The maximum amount of WP in 4th replication was 0.53 kg m^{-3} ha^{-1}. The average amount of optimum WP and crop yield was 0.51 kg m^{-3} ha^{-1} and 3575.0 kg ha^{-1} in 2010 and 2011, respectively.

If the priority of objective functions changes that is if WP objective function is more important than crop yield objective function, then the optimum results will change. In the second scenario, variation trend of average distance changes between 10 and 45 among consecutive results (Figure 7). This variation trend in consecutive results shows that as we move toward the next generation, the distance between optimum results become less and they tend to converge. Figure 8 shows Pareto front curve in the second scenario. The horizontal axis in Figure 8 is chosen to show the amounts of the first objective function (the amount of crop yield) and the amount of the second objective function (The amount of WP) on the vertical axis. The amounts of WP change from 0.88 to 1.02 kg.m^{-3} ha^{-1}. Also, the amounts of crop yield change from 2800 to 4000 kg ha^{-1}. The amounts of joint optimum objective functions for the last seven consecutive replications by using MOGA are given in Table 6.

According to Table 6, the best amount of optimum crop yield is 3838.1 kg ha^{-1} in replication number one. Replication number five is 2995.0 kg ha^{-1} among the last 7 consecutive replications. Replications number one and seven have the highest amounts of WP among last seven consecutive replications. In the second scenario, replication number one has the best result among last seven replications with crop yield of 3838.0 kilograms per hectare and WP of 1.124 kg.m^{-3} ha^{-1}. Shibo et al. (2008) reported a direct relationship between objective functions using the amounts of optimum irrigation water in the combined optimization of objective functions that conforms to the result of this research.

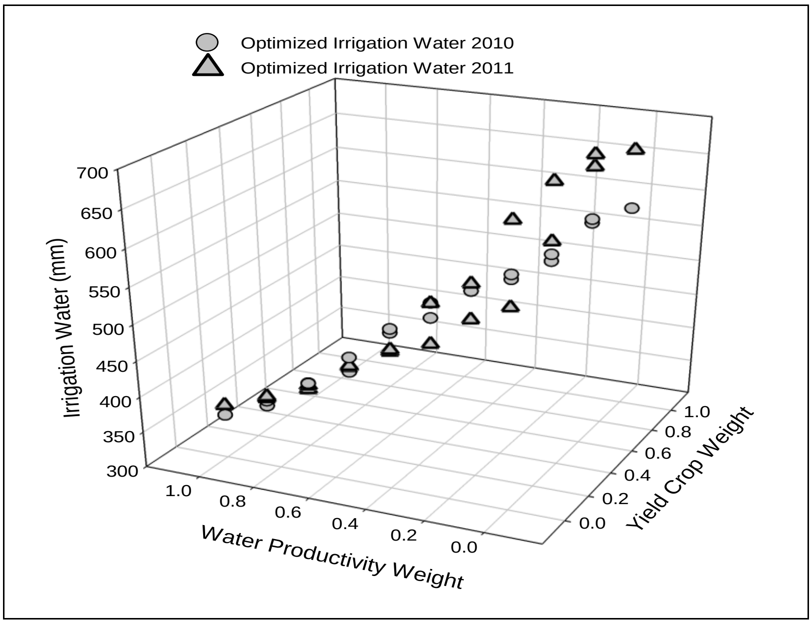

Figure 7. Changes of the amount of irrigation water in relation to objective function weights

Table 6. The optimum amounts of irrigation water and objective functions in the second scenario

Replication No.	The Optimum Irrigation Water (mm)		The Optimum Crop Yield (kg/ha)		The Optimum WP (kg/m^3)	
	2010	2011	2010	2011	2010	2011
1	569.21	594.58	3838.1	3902.72	1.124	0.75
2	633.33	621.49	3815.56	3898.8	0.987	0.721
3	615.64	607.54	3333.44	3312.93	0.996	0.594
4	590.42	611.36	3814.00	3831.9	1.044	0.706
5	530.92	552.7	2995.04	3195.76	0.987	0.673
6	538.29	546.91	3275.40	3087.22	0.993	0.583
7	588.95	578.45	3819.57	3796.85	1.023	0.645

The constraint of this problem includes the range of the amount of irrigation water. This constraint is the upper and lower limits for the possible amount of irrigation water. These limits are based on the possible amount in water stress treatments are equal to 200 to 700 millimeters, respectively. Considering MOGA programming codes, WP objective function is written inversely so that the amounts of optimum WP in Figure 6 for each point is reversed. That is WP in the Tables 5 and 6 are obtained by dividing one to WP in Figures 4a to 4d and 5a to 5d.

Comparison of measured and optimal WP and crop production with each other and optimum WP and crop production in two consecutive years

SPSS software version 9.0 was used for statistical analysis of optimal solutions of the model and observed field data. The amount of crop production and WP for each existing irrigation treatment was determined by using MOGA model. These two series data (measured and optimized dataset during two agronomical years 2010 and 2011) as an order pair in the comparison part of means test in SPSS software were compared with each other by using t-test. According to Table 7, 8, and 9 also considering P-value is larger than the amount of tabular t at the significance level, H0 is acceptable an as a result the amounts of mean optimal crop production and WP in two agronomical years is not significant, compared with the amount of mean crop production and WP. Also, the results show that the optimums in these two years did not have significant differences.

Table 7. Paired Samples Statistics

Paired Dataset		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	field	3529.7538	14	64.78428	178.27628
Pair 1	MOGA	3442.1546	14	29.83649	81.21823
Pair 1	SA				

Table 8. Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	field & MOGA	28	0.7532	0.446
Pair 1	field & SA			

Table 9. Paired Samples Test by using T-Test in SPSS

	Paired Differences					t	df	P_{value}
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
				Lower	Upper			
field - MOGA	87.59921	765.58186	212.33420	-560.98402	736.18244	0.413	27	0.687
field - SA								

The results of optimization using SA (Simulated Annealing) algorithm

Equation 8 and equation 9 have used as SA optimization functions separately. For obtaining optimum Pareto front, the weights given to WP and crop production functions have been changed. For this purpose, considering the importance of each function, different weights have given to each and different results that were the same as optimum Pareto, were obtained. To start, number one was given to the less important objective function and the other objective function was given integer weights with a continuous increase so that a set of optimum Pareto front results were obtained. In the next stage, in view of the importance the place of objective function and the weights were changed so that Pareto optimum results were completed. Table 10 shows the Pareto optimum results for 2010 and 2011.

Table 10. Pareto optimum results were extracted by SA algorithm

Replication No.	ω_1 (Crop Yield Weighting)	ω_2 (Water Productivity Weighting)	The Optimum Irrigation Water (mm)		The Optimum Crop Yield (kg/ha)		The Optimum WP (kg/m^3)	
			2010	2011	2010	2011	2010	2011
1	0	1	361.8	375.8	3428.6	3183.3	0.806	0.816
2	0.1	0.9	374.4	377.8	3396.4	3180.5	0.779	0.812
3	0.2	0.8	391.0	388.1	3361.7	3168.9	0.745	0.792
4	0.3	0.7	421.1	408.9	3321.5	3158.3	0.689	0.754
5	0.4	0.6	449.1	424.7	3310.4	3161.9	0.644	0.728
6	0.5	0.5	484.5	425.6	3332.5	3162.3	0.596	0.726
7	0.6	0.4	494.7	453.7	3346.3	3194.2	0.584	0.685
8	0.7	0.3	504.5	464.3	3362.9	3214.4	0.573	0.671
9	0.8	0.2	533.4	551.2	3429.4	3550.2	0.545	0.589
10	0.9	0.1	576.4	664	3578.6	4445	0.517	0.57
11	1	0	585.7	664.9	3618.9	4446.0	0.513	0.574

Table 10 indicates that by changing the allocated weights of both WP and crop production functions the amounts of irrigation water also change. For extracting 11 points of Pareto front, the weight allocated to crop production function was increased from zero to one and the weight allocated to WP function decreased from one to zero. In results number 1 and 11 in Table 10 with the allocated weights of zero and one to two objective functions, the problem changed to a single objective one. In result number 1 which only considered WP function, the optimum results were moved toward the minimum amount of irrigation water. Moreover, in result number 11 which only considered crop production function, the optimum result moved toward the maximum amount of irrigation water. Figure 6 shows that the trend of changes of the optimum amount of irrigation water with the objective function weight changes. Figure 6 show that when allocated weight to crop production increases, the amount of irrigation water also increases. The reason for this is the direct relationship between irrigation water and crop production. Also, when the weight of WP function increases, the optimum amount of irrigation water decreases because of the inverse relationship between the amount of irrigation water and WP. Figure 7 (Pareto a and Pareto b) shows Pareto front results for 2010 and 2011.

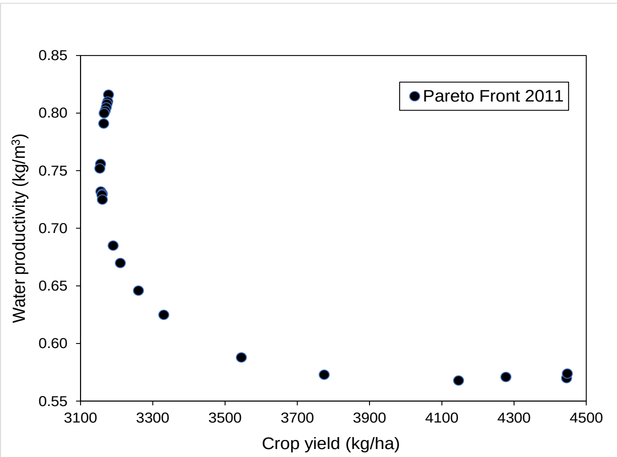

Figure 8a. The optimum results of SA algorithm at 2011

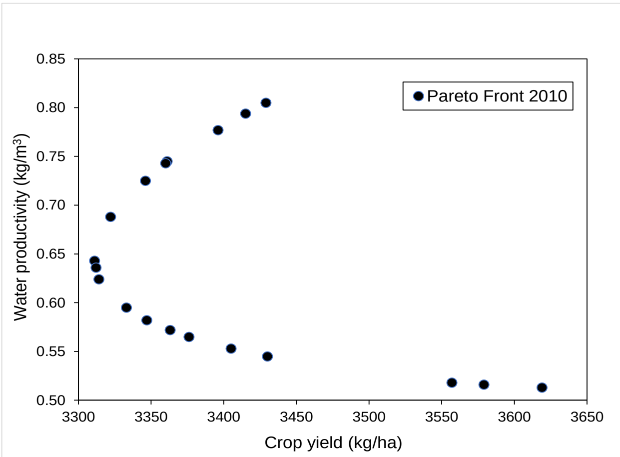

Figure 8b. The optimum results of SA algorithm at 2010

The Pareto front results at 2010 (Figure 8a) shows that crop production ranges from about 3310 to 3619 kg ha^{-1} and WP from 0.51 to 0.81 $kg.m^{-3}$ ha^{-1}. The best crop production was obtained for 3618.9 kg/ha for consuming 585.7 mm irrigation water during growing season. Also, the best result for WP was consuming 316.8 mm irrigation water (Table 10). The point to notice in those Pareto front results of Figure 8a was the lower amounts of the maximum optimized crop production than actual crop production and the higher maximum optimized WP than actual WP (Table 10). In Figure 7b, maximum crop production was 4446 kg ha^{-1} for consuming 664.9 mm irrigation water. Also, the maximum WP was 0.816 $kg.m^{-3}$ ha^{-1} for consuming 375.8 mm irrigation water. Considering Table 10, crop production and WP under actual conditions are less than the optimized amounts by using SA algorithm with 2011. Another important point common in Figures 8a and 8b, was the absence of optimum results at special distances of crop production (3450 to 3550 kg ha^{-1} for Figure 7a and 3800 to 4100 kg ha^{-1} for Figure 8b) among the optimum results.

Comparing the results of MOGA and SA algorithm

Comparison of the obtained MOGA results and single objective SA algorithm (Tables 5, 6 and 10) show that MOGA has a better capability of simultaneous optimization of WP and crop production functions. For example, the maximum crop production achievement and WP among optimized results in 2010 (Table 6) are 3818.1 kg/ha and 1.124 kg/m^3, respectively. However, in SA algorithm, these results are 3428.6 kg/ha and 0.806 kg/m^3. Also, the maximized results of the objective functions are near the actual amounts in MOGA. One of the reasons for the weaker SA algorithm results is due to the way of allocation of weights to objective functions.

To combine the weights of functions to reach the strong Pareto front a suitable method is required. We cannot obtain suitable optimum results at the non-convex parts of Pareto front by combining objective functions. In other words, the condition to reach the best optimum results in weighted sum method is convexity of the feasible results (Miettinen, 1999; Ghodspour et al., 2021).

CONCLUSIONS

In this research, a systematic survey of the two Evolutionary Algorithms on a deficit irrigation problem as staged water stress treatment has been presented. This kind of optimization leads to making a collection of optimum results instead of one because there isn't any individual result that optimizes all objective functions considering all objective functions simultaneously. Two problems in optimized results in using SA algorithm by converting multi-objective to one objective problem method are expressed. First, Pareto results don't have a suitable distribution which was reported by different authors. Second, due to unsuitable results of this method in non-convex results space, the optimized results in this method were unsuitable compared to MOGA results. In recent years, it is recommended that in this optimization approach, in addition to grain yield and water WP, three items of energy, economic benefit and adaptation to the effects of climate change be added, and a simultaneous optimization of at least five goals be performed.

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