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Artificial neural networks and multicriterion analysis for sustainable irrigation planning

K. Srinivasa Raju[a], D. Nagesh Kumar[b,*], Lucien Duckstein[c]

[a]*Civil Engineering Department, Birla Institute of Technology and Science, Pilani 333 031, Rajasthan, India*
[b]*Department of Civil Engineering, Indian Institute of Science, Bangalore 560 012, India*
[c]*ENGREF, 19 Avenue Du Maine, 75732 Paris Cedex 15, France*

Abstract

The objective of the present paper is to select the best compromise irrigation planning strategy for the case study of Jayakwadi irrigation project, Maharashtra, India. Four-phase methodology is employed. In phase 1, separate linear programming (LP) models are formulated for the three objectives, namely, net economic benefits, agricultural production and labour employment. In phase 2, nondominated (compromise) irrigation planning strategies are generated using the constraint method of multiobjective optimisation. In phase 3, Kohonen neural networks (KNN) based classification algorithm is employed to sort nondominated irrigation planning strategies into smaller groups. In phase 4, multicriterion analysis (MCA) technique, namely, Compromise Programming is applied to rank strategies obtained from phase 3. It is concluded that the above integrated methodology is effective for modeling multiobjective irrigation planning problems and the present approach can be extended to situations where number of irrigation planning strategies are even large in number.

Keywords: Irrigation planning; Linear programming; Kohonen neural network; Multicriterion analysis

1. Introduction

Water resources are becoming scarce, due to growing population and changing life styles, increase in demands from industry, contamination of available water resources, resulting from human activities,

* Corresponding author.
E-mail addresses: ksraju@bits-pilani.ac.in (K.S. Raju), nagesh@civil.iisc.ernet.in (D.N. Kumar), duckstein@engref.fr (L. Duckstein).

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etc. This reduces the share of water available for irrigation. Also conflicting nature of irrigation planning objectives is making the problem more complex. For developing countries, multiple irrigation planning objectives are also more important than mere maximisation of a single objective. This necessitates irrigation planning in the multiobjective framework, so that suitable and sustainable strategies can be developed for practical implementation. Multicriterion analysis (MCA) has been proved to provide a good framework for effective decision making, for selecting the best compromise among the available alternatives [1]. The objective of the present paper is to integrate MCA with real world irrigation planning problem, to select the most suitable and sustainable irrigation planning strategy. Numerous researchers worked on MCA for various water resources planning problems such as river basin planning [2,3], hydropower operation [4] ground water planning [5], water resources strategies [6,7] and irrigation planning [8–12].

An artificial neural network (ANN) is a massively parallel distributed information processing system resembling biological neural networks of the human brain [13] and can be used for storing and recalling data, classifying patterns, performing general mapping from input pattern to output pattern and grouping similar patterns [14]. Neural networks follow two types of learning process, namely, supervised and unsupervised. In supervised learning, network acquires knowledge by comparing the predicted output with the known output. Data sets, consisting of input and output, are used to adjust the connection strengths during training over a number of epochs. In unsupervised learning, network does not require the knowledge of corresponding output, for comparison and learning. Through repeated epochs, the learning algorithm adjusts the connection strengths and causes the network, to represent a simplified feature map of the characteristics [13,14].

The present study deviates from the previous ones, in that it includes application of Kohonen neural networks (KNN), for the sorting of nondominated irrigation planning strategies and integration of KNN analysis with MCA for irrigation planning problems. In this paper, a four-phase methodology is employed for irrigation planning problem. In phase 1, three separate linear programming (LP) based irrigation planning models are formulated for maximisation of net economic benefits (*BE*), agricultural production (*PR*) and labour employment (*LM*). In phase 2, nondominated (compromise) irrigation planning strategies are generated, using the constraint method of multiobjective optimisation. In phase 3, KNN based classification algorithm is employed to sort the nondominated irrigation planning strategies into small groups. In phase 4, MCA technique, namely, distance based compromise programming (CP), is applied to rank the irrigation planning strategies, obtained from phase 3. Fig. 1 presents the flow chart of the methodology.

2. Case study

The above four-phase methodology is applied to a case study of Jayakwadi irrigation project on river Godavari, Maharashtra, India, which consists of a two-reservoir system, namely, Paithan and Mazalgaon. Fig. 2 presents a schematic diagram of the Jayakwadi project. Two canals are originating from Paithan reservoir and are called Paithan left bank canal (PLBC) having culturable command area (CCA) of 142,000 hectare (ha) and Paithan right bank canal (PRBC) having culturable command area of 42,000 ha. Paithan reservoir has a gross storage capacity of $2909 \times 10^6\,\mathrm{m}^3$ and live storage of $2170 \times 10^6\,\mathrm{m}^3$. The Mazalgaon reservoir is located downstream of PRBC. It has a gross storage capacity of $453.64 \times 10^6\,\mathrm{m}^3$, and live storage of $311.30 \times 10^6\,\mathrm{m}^3$. It has an additional supply source from Sindphana River, a tributary of

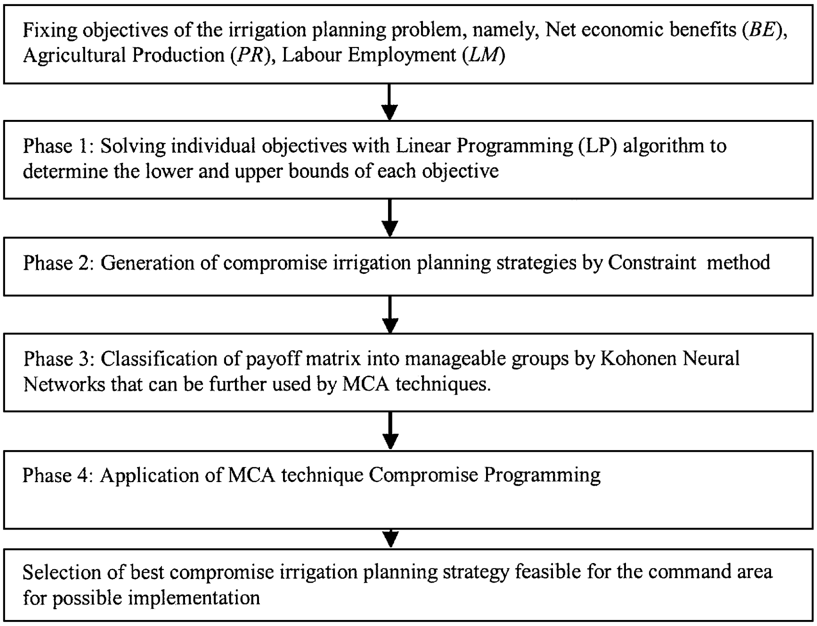

Fig. 1. Flow chart of the methodology.

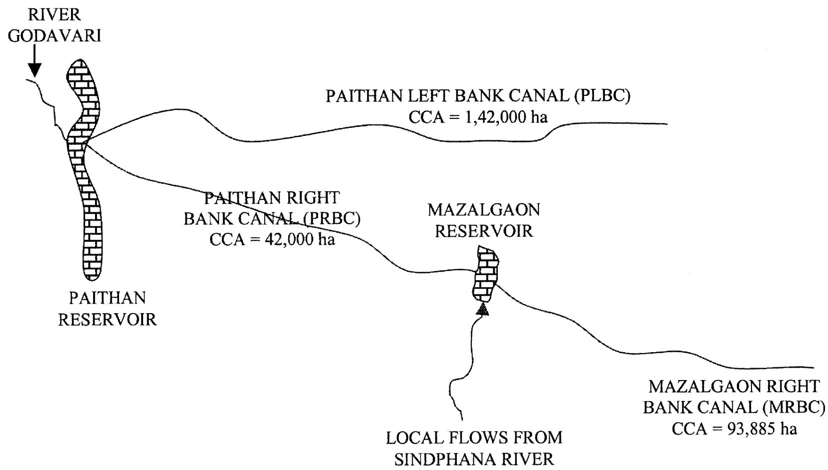

Fig. 2. Schematic diagram of Jayakwadi irrigation project.

Godavari River. The right bank canal (MRBC) of Mazalgaon reservoir has a command area of 93,885 ha. The main crops under irrigation are sugar cane, banana, chillies, cotton, sorghum, paddy, wheat, gram and groundnut.

2.1. *Mathematical modeling for achieving lower and upper bounds (phase 1)*

LP based optimisation models [15] are formulated in the present analysis. The three objectives to be maximised are, *BE*, *PR* and *LM*.

Objective 1: The net *BE* under different crops, from the command areas of PLBC, PRBC and MRBC are to be maximised. These are obtained by deducting the cost of surface water from the gross economic benefits of crops (excluding costs of fertilisers, labour employment, etc.) and can be expressed as

$$BE = \sum_{i=1}^{10} BL_i AL_i + \sum_{i=1}^{10} BR_i AR_i + \sum_{i=1}^{10} BM_i AM_i - C_w \sum_{t=1}^{12} (RLR_t + RM_t), \tag{1}$$

where i is the Crop index [1 = sugar cane (SC;P), 2 = banana (BA;P), 3 = chillies (CH;TS), 4 = cotton (CT;TS), 5 = sorghum (SO;S), 6 = paddy (PA;S), 7 = sorghum (SO;W), 8 = wheat (WH;W), 9 = gram (GR;W), 10 = groundnut (GN;HW), first term in crop index represents crop notation and second term, for season in which it is grown], S = summer, W = winter, TS = two season, HW = hot weather, P = perennial, t = time index (1 = January, ..., 12 = December). BE = Net economic benefits from the planning region (Indian Rupees); BL_i, BR_i, BM_i = Rate of gross economic benefits from the crops (excluding costs of fertilisers, labour employment, etc) from the command areas of PLBC, PRBC and MRBC, respectively, in Indian Rupees per ha.; AL_i, AR_i, AM_i = Area of crop i grown in the command areas of PLBC, PRBC and MRBC (ha); C_w = Cost of surface water (Rs/$10^6\,m^3$); RLR_t = Total water releases from Paithan reservoir to command areas of PLBC and PRBC ($10^6\,m^3$); RM_t = Water releases from Mazalgaon reservoir to command area of MRBC ($10^6\,m^3$).

Objective 2: *PR* of all the crops, for the whole planning area, is to be maximised and can be expressed as

$$PR = \sum_{i=1}^{10} Y_i (AL_i + AR_i + AM_i), \tag{2}$$

where *PR* is the agricultural production (tons) and Y_i the yield of the crop i (tons / ha).

Objective 3: Labour employment for each crop i, for the whole year for the whole planning area is to be maximised and can be expressed as

$$LM = \sum_{t=1}^{12} \sum_{i=1}^{10} L_{it} (AL_i + AR_i + AM_i), \tag{3}$$

where *LM* is the labour requirement for whole planning horizon (Man-Days) and L_{it} the labour requirement for crop i in month t (Man-Days) per hectare.

The above three objectives are subject to the following constraints.

2.1.1. *Paithan reservoir scheme*

1. *Continuity equation:*

Reservoir operation includes water transfer, storage, inflow and spillage activities. Water transfer activities considered are transport of water from the reservoir to the producing areas, through canals to meet the water needs. A monthly continuity equation for the reservoir storage ($10^6\,\mathrm{m}^3$) can be expressed as

$$SLR_{t+1} = SLR_t + I_t - ELR_t - RLR_t - OLR_t, \quad t = 1, 2, \ldots, 12, \tag{4}$$

where SLR_{t+1} = storage in the Paithan reservoir ($10^6\,\mathrm{m}^3$) at the end of month t; I_t = Inflows into the reservoir ($10^6\,\mathrm{m}^3$); ELR_t = Evaporation loss ($10^6\,\mathrm{m}^3$); RLR_t = Total release into the canals; OLR_t = Overflow from the reservoir ($10^6\,\mathrm{m}^3$).

This constraint assumes that the monthly inflows into the reservoir are known with certainty. When stochasticity is incorporated, the above equation changes to

$$\Pr(SLR_{t+1} - SLR_t + ELR_t + RLR_t + OLR_t \geqslant I_t) \geqslant \alpha, \quad t = 1, 2, \ldots, 12. \tag{5}$$

Eq. (5) can be re-written as

$$SLR_{t+1} - SLR_t + ELR_t + RLR_t + OLR_t \geqslant I_t^{\alpha}, \quad t = 1, 2, \ldots, 12, \tag{6}$$

where I_t^{α} is inverse of the cumulative distribution of inflows at dependability level α (in which stochastic considerations are included).

2. *Crop area restrictions:*

The total area under different crops in PLBC command area, in a particular season, should be less than or equal to the CCA

$$\sum_i AL_i \leqslant \mathrm{CCA}, \quad i = 1, 2, 3, 4, 5, 6 \quad \text{Summer season}, \tag{7}$$

$$\sum_i AL_i \leqslant \mathrm{CCA}, \quad i = 1, 2, 3, 4, 7, 8, 9 \quad \text{Winter season}, \tag{8}$$

$$\sum_i AL_i \leqslant \mathrm{CCA}, \quad i = 1, 2, 7, 8, 9, 10 \quad \text{Hot weather season}. \tag{9}$$

Crops 1,2 are perennial and so present in all the seasons; Crops 3,4 are two-season crops present in the Summer and Winter seasons; Crops 7, 8 and 9 sown in winter extend to a part of hot weather season.

3. *Crop water releases:*

Monthly crop water releases CWR_{it} are obtained from the Jayakwadi project report. When any crop activity is absent CWR_{it} becomes zero. Total water releases from Paithan reservoir must satisfy the irrigation demands of PLBC and PRBC

$$RLR_t - \sum_{i=1}^{10} CWR_{it} AL_i - \sum_{i=1}^{10} CWR_{it} AR_i = 0, \quad t = 1, 2, \ldots, 12, \tag{10}$$

where CWR_{it} is the Crop water releases (meters) for crop i in month t.

4. *Canal capacity restrictions:*

Releases into PRBC, should not exceed its capacity. Similarly releases into PLBC should not exceed its capacity.

$$\sum_{i=1}^{10} CWR_{it}AR_i + OLR_t \leqslant CCR, \quad t = 1, 2, \ldots, 12, \tag{11}$$

$$\sum_{i=1}^{10} CWR_{it}AL_i \leqslant CCL, \quad t = 1, 2, \ldots, 12, \tag{12}$$

where *CCL, CCR* are the canal capacities of PLBC and PRBC ($10^6\,\mathrm{m}^3$).

5. *Live storage restrictions:*

Reservoir storage volume SLR_t in any month t, must be less than or equal to live storage of the reservoir

$$SLR_t \leqslant LSP, \quad t = 1, 2, \ldots, 12, \tag{13}$$

where *LSP* is the live storage of Paithan reservoir ($10^6\,\mathrm{m}^3$).

2.1.2. Mazalgaon reservoir scheme

6. *Continuity equation:*

$$SM_{t+1} = SM_t + IM_t - EM_t - RM_t - OM_t + OLR_t, \quad t = 1, 2, \ldots, 12, \tag{14}$$

where SM_{t+1} is the storage in the Mazalgaon reservoir ($10^6\,\mathrm{m}^3$) at the end of month t, IM_t the inflows into the reservoir ($10^6\,\mathrm{m}^3$), EM_t the evaporation loss ($10^6\,\mathrm{m}^3$) and OM_t the overflows from Mazalgaon reservoir ($10^6\,\mathrm{m}^3$). The above constraint assumes that the monthly inflows into the reservoir are known with certainty. When stochasticity is incorporated in the inflow terms, the above equation changes to

$$SM_{t+1} - SM_t + EM_t + RM_t + OM_t - OLR_t \geqslant IM_t^{\alpha}, \quad t = 1, 2, \ldots, 12, \tag{15}$$

where IM_t^{α} is the inverse of the cumulative distribution of inflows at reliability level α.

7. *Releases from Mazalgaon reservoir must satisfy the irrigation demands of MRBC:*

$$RM_t - \sum_{i=1}^{10} CWR_{it}AM_i = 0, \quad t = 1, 2, \ldots, 12. \tag{16}$$

8. *Irrigation demands of MRBC must be less than its capacity:*

$$RM_t \leqslant CCM, \quad t = 1, 2, \ldots, 12, \tag{17}$$

where *CCM* is the canal capacity of MRBC ($10^6\,\mathrm{m}^3$).

9. *Live storage restrictions:*

Reservoir storage volume SM_t in any month t, must be less than or equal to live storage of Mazalgaon reservoir

$$SM_t \leqslant LSM, \quad t = 1, 2, \ldots, 12, \tag{18}$$

where LSM is the live storage of Mazalgaon reservoir ($10^6\,\mathrm{m}^3$).

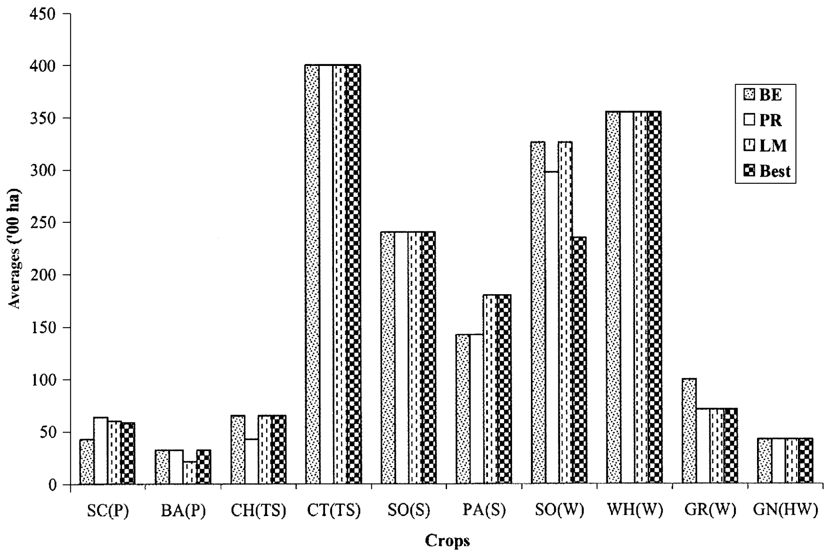

Fig. 3. Cropping pattern of PLBC.

Important decision variables of the irrigation planning model are areas of crops in the three command areas PLBC, PRBC, MRBC and monthly reservoir releases and storages in the Paithan and Mazalgaon reservoirs. In the present study 75% dependable inflow level (α) is considered for both the reservoirs and these are amounting to annual values of $2451.7 \times 10^6\,m^3$ and $400.9 \times 10^6\,m^3$, respectively.

Initially, three objective functions, i.e., net economic benefits, agricultural production and labour employment are maximised separately, as single objective LP problems. This enables to determine the cropping pattern, storage, release policies and lower and upper bounds that can be achieved for each objective. Individual optimal cropping plans for the regions of PLBC, PRBC and MRBC, as obtained by the three planning objectives are presented in Figs.3–5, respectively. It is observed from these figures that there is no change in acreage of cotton (ts), sorghum (s), wheat (w) and groundnut (hw) for the different planning objectives. However, significant change is observed in gram (w) in case of *BE* as compared to other scenarios.

Table 1 presents derived parameters of the irrigation planning problem such as irrigated area, annual releases, net economic benefits, agricultural production and labour employment to meet the above three planning objectives. The notations 'U' and 'L' represent the upper and lower bounds, for each planning objective, which will be utilised in phase 2 of the multiobjective optimisation, to generate compromise irrigation planning strategies.

It is also observed that the three objectives for all the three areas of PLBC, PRBC and MRBC satisfied the minimum crop acreages, while optimising the crop acreages. It can be seen from the above analysis that the three planning objectives are conflicting (as observed from Table 1), which necessitates development of trade-off relationships, for finding a best compromise (nondominated) irrigation planning strategy.

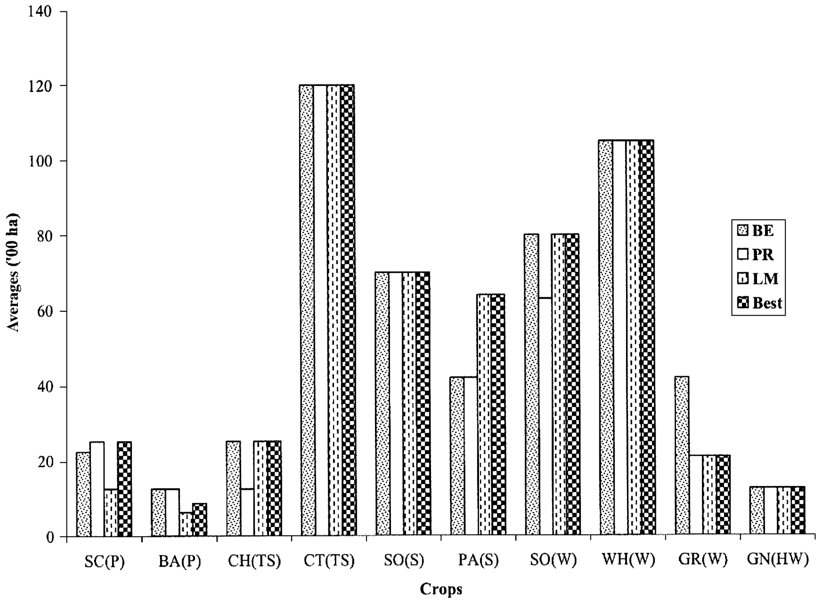

Fig. 4. Cropping pattern of PRBC.

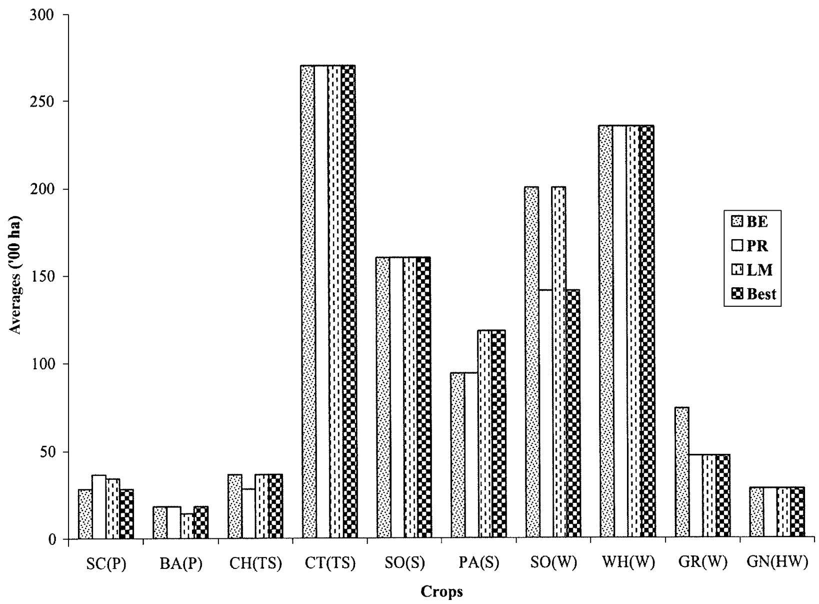

Fig. 5. Cropping pattern of MRBC.

Table 1
Derived parameters of the irrigation planning problem

Parameters	For maximisation of			
	Net economic benefits	Agricultural production	Labour employment	Best Comp Irri. Plng. Stra (S1)
Irrigated area (hundreds of ha)				
Paithan left bank canal (PLBC)	1746.00	1687.50	1761.30	1679.76
Paithan right bank canal (PRBC)	531.80	484.00	516.70	531.72
Mazalgaon right bank canal (MRBC)	1144.00	1058.00	1142.90	1082.00
Annual releases (10^6 m^3)				
Paithan reservoir	1628.06	1647.44	1616.36	1652.93
Mazalgaon reservoir	793.31	773.93	805.01	768.44
Net economic benefits (10^6 Rs.)	2118.70^{U}	2094.00	1914.00^{L}	2053.80
Agricultural production (10^6 tons)	1.9570^{L}	2.2393^{U}	1.9870	2.0879
Labour employment (10^6 Man-Days)	35.5460	34.0770^{L}	37.1220^{U}	35.9040

2.2. Generation of nondominated irrigation planning strategies using constraint method (phase 2)

Constraint method is a plan generation technique. It operates by optimising one objective while all others are constrained to some value. Mathematically it can be expressed [16] as

$$\max f_h(\mathrm{x}) \tag{19}$$

subject to

$$f_r(\mathrm{x}) \geqslant L_r; \quad r = 1, 2, \ldots, h-1, h+1, \ldots, p \tag{20}$$

and existing constraints.

In the method, hth objective function is chosen for maximisation, from among p objectives. $f_h(\mathbf{x})$ and $f_r(\mathbf{x})$ are objective functions corresponding to objectives h and r. Maximum (Z_{U}) and minimum values (Z_{L}), that can be obtained by each objective, can be used to formulate different values of L_r (L_r is bound on objective r which is later transformed as constraint in the constraint method), for generation of nondominated solutions, based on preferences of decision maker and analyst.

Constraint method of multi objective optimisation is employed to generate nondominated irrigation planning strategies. In the present study, weights of the three objectives are taken as equal. Maximisation of net economic benefits is selected as the main objective, in the constraint method formulation and the other two objectives, agricultural production and labour employment are placed as the constraints in the constraint set. The nondominated set of irrigation planning strategies is generated, by parametrically varying the bounds (between lower and upper bounds in Table 1) of the constraints (transformed objective functions of agricultural production and labour employment). Nineteen irrigation planning strategies (generated by varying the bounds), from the constraint method are presented in Table 2.

Table 2
Nondominated irrigation planning strategies (payoff matrix)

Strategy number	Labour employment (10^6 Man-Days)	Agricultural production (10^6 tons)	Net economic benefits (10^6 Rs.)
A01	35.5990	2.1132	2088.40
A02	35.9040	2.0879	2053.80**
A03	36.0560	2.0753	2036.30
A04	36.2080	2.0627	2018.80
A05	36.5130	2.0375	1983.80
A06	36.6650	2.0249	1966.30
A07	36.8170	2.0123	1948.80**
A08	36.9500	2.0000	1935.00
A09	37.1220	1.9870	1914.00
A10	37.1020	1.9850	1920.00**
A11	37.0000	1.9843	1941.30
A12	36.9450	1.9830	1953.80
A13	36.7870	1.9810	1987.60
A14	36.7100	1.9795	2004.70**
A15	36.6300	1.9780	2022.40
A16	36.4700	1.9750	2057.80
A17	36.3920	1.9730	2075.50
A18	36.3150	1.9720	2092.10**
A19	35.5460	1.9570	2118.70

2.3. Classification of irrigation planning strategies using Kohonen neural networks (phase 3)

Kohonen neural network is a self organising mapping technique with only two layers, input and output layers. Each layer is made up of neurons. The number of neurons in input layer M, is identical to the dimensionality of input vectors while the number of neurons in the output layer N, is determined by the number of groups that input data will be partitioned into. Each neuron in the output is fully interconnected with those in input layer by a set of weights or a weight vector, e.g., the jth output neuron has a weight vector connecting to input neurons, $W_j = \{W_{ji} \mid i = 1, 2, \ldots, M\}$. The function of an input neuron is transmitting input data to the next layer, whereas an output neuron calculates the Euclidean distance between its weight vector W_j and input vector X to measure their similarity. The main objective of Kohonen network [17–21] is to transform an incoming vector with arbitrary dimension into a one- or two-dimensional discrete map, and to perform this transformation adaptively in a topologically ordered fashion. The Kohonen neural network training procedure is as follows:

1. *Initialization:* Assign randomly small values to the initial weight vectors $W_j(0)$ of output neuron j, where $j = 1, 2, \ldots, N$.

2. *Sampling:* Draw an input vector X randomly from the input data, and feed it into the Kohonen network.

3. *Similarity computing:* Find distance between input vector X and each output neuron's weight $W_j(n)$ at time n.

$$D_j = || X - W_j ||; \; j = 1, 2, \ldots, N, \text{ where } ||.|| \text{ is Euclidean norm.}$$

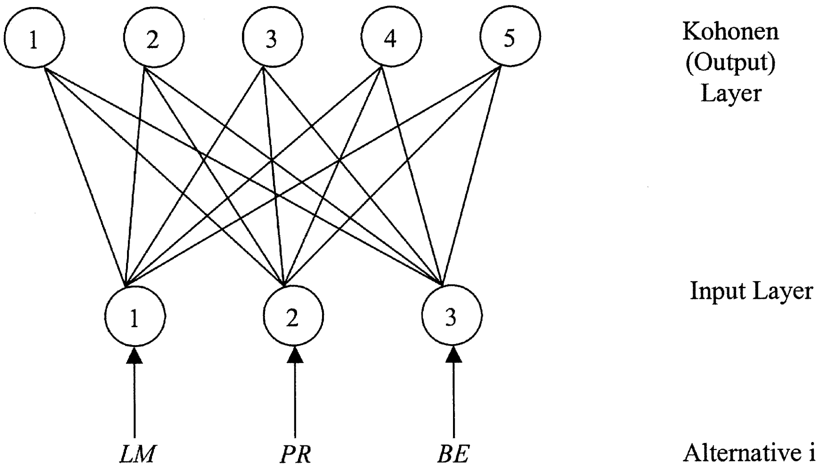

Fig. 6. Kohonen neural networks for irrigation planning problem.

4. *Competition:* Select the winning neuron C which has minimum of D_j.

$$C = \arg_j \min(D_j);\ j = 1, 2, \ldots, N.$$

5. *Updating:* Adjust the weight vectors of all neurons through

$$w_j(n+1) = w_j(n) + \eta(n)[X(n) - W_j(n)] \text{ if } \in A'_c$$
$$w_j(n+1) = w_n(n) \text{ otherwise}$$

$$C = \arg_j \min(D_j);\ j = 1, 2, \ldots, N,$$

where, $\eta(n)$ is the learning rate parameter, and A'_C is the neighbourhood function centred on the winning neuron C.

6. *Iteration:* Repeat steps (2)–(5) until no noticeable changes in the feature map are observed or when the specified number of epochs are achieved [18,21].

In the present study, self organising map (SOM) networks, proposed by Kohonen [17,18,21] referred as KNN in this paper, are used to classify the nondominated irrigation planning strategies, obtained from phase 2 and the resulting representative strategies are used as inputs to MCA. MATLAB-based solution methodology is employed in the present study [19]. Detailed description of KNN is available in [17–21].

Fig. 6 presents schematic diagram of KNN for the present irrigation planning problem. Input layer consists of 3 variables, i.e. *LM, PR* and *BE*. Number of nodes in Kohonen layer is five. Table 3 presents the normalised payoff matrix (based on the lower and upper bounds in Table 1) and resulting groups obtained from Kohonen classification. Kohonen learning rate and number of epochs are fixed as 0.01 and 5000, respectively. Initially all the weight vectors and biases for each node are considered as random values. KNN is run with 4, 5 and 6 groups and corresponding squared dispersion values are found to be 0.6198, 0.3538 and 0.3404, respectively. More number of groups are not tried, since the size of payoff matrix is small. It is felt that group (node) size of 5 is reasonable, as there is not much difference between dispersion values of groups 5 and 6. It is also observed, that there is no change in the values of weight vectors and biases, for each node after 5000 epochs. Squared deviations, between weight vector of that group and

Table 3
Normalised payoff matrix and representative group from Kohonen classification

Strategy number	Labour employment	Agricultural production	Net economic benefits	Dispersion from weight vector	Group
A01	0.50	0.55	0.85	0.05373	1
A02	0.60	0.46	0.68	0.00022	1[a]
A03	0.65	0.42	0.60	0.00764	1
A04	0.70	0.37	0.51	0.04072	1
A05	0.80	0.29	0.34	0.04192	4
A06	0.85	0.24	0.26	0.00514	2
A07	0.90	0.20	0.17	0.00287	2[a]
A08	0.94	0.15	0.10	0.00354	3
A09	1.00	0.11	0.00	0.00531	3
A10	0.99	0.10	0.03	0.00186	3[a]
A11	0.96	0.10	0.13	0.00420	3
A12	0.94	0.09	0.19	0.01422	2
A13	0.89	0.09	0.36	0.01032	4
A14	0.86	0.08	0.44	0.00189	4[a]
A15	0.84	0.07	0.53	0.00967	4
A16	0.79	0.06	0.70	0.07131	4
A17	0.76	0.06	0.79	0.00908	5
A18	0.73	0.05	0.87	0.00261	5[a]
A19	0.48	0.00	1.00	0.06752	5
				Total dispersion from weight vector 0.3538	

[a]Representative irrigation planning strategy for the corresponding group.

normalised strategies in that group for each criterion, are calculated. The summation of these squared deviations for all criteria gave the total squared deviation, corresponding to each irrigation strategy in that group. For example, the normalised values of three criteria, labour employment, agricultural production and net economic benefits for A02 are 0.60, 0.46 and 0.68. Corresponding weight vector for that group (node) are 0.6076, 0.4544 and 0.6683. Squared deviation of A02 from weight vector is calculated as $[(0.60 - 0.6076)^2 + (0.46 - 0.4544)^2 + (0.68 - 0.6683)^2] = 0.00022$. Irrigation strategy that gives the minimum squared deviation is chosen as the representative irrigation strategy for that group. The strategies A02, A07, A10, A14, A18 of Table 3 having minimum squared deviations from corresponding weight vectors of 0.00022, 0.00287, 0.00186, 0.00189 and 0.00261 are found to be the representative strategies for the five groups (Table 3). Table 4 presents irrigated area and annual releases corresponding to the above five representative irrigation strategies. Effect of learning rate on the squared dispersion value in case of KNN is also studied. It is observed from Fig. 7 that squared dispersion value is in the range of 0.3–0.38 for a learning rate of 0.01–0.5, with steep increase to 0.48 for learning rate of 0.6 and almost same up to learning rate of 0.7. Steep rise is observed thereafter, indicating necessity for careful selection of the learning rate.

2.4. Application of multicriterion analysis (MCA) technique (phase 4)

Multicriterion analysis technique, namely, distance based compromise programming (CP) [2,3,10,22], is used in the present study. CP defines the ‘best’ solution as the one in the set of solutions, whose point

Table 4
Summary of representative irrigation planning strategies

Group number	Irrigated area (hundreds of ha)			Annual releases from reservoir (10^6 m^3)	
	PLBC	PRBC	MRBC	Paithan	Mazalgaon
S1	1679.76	531.73	1082.00	1652.93	768.44
S2	1760.40	529.29	1100.00	1655.89	765.48
S3	1754.17	527.93	1137.63	1634.00	787.37
S4	1750.08	535.59	1102.07	1642.58	778.80
S5	1741.08	535.59	1080.54	1654.07	767.30

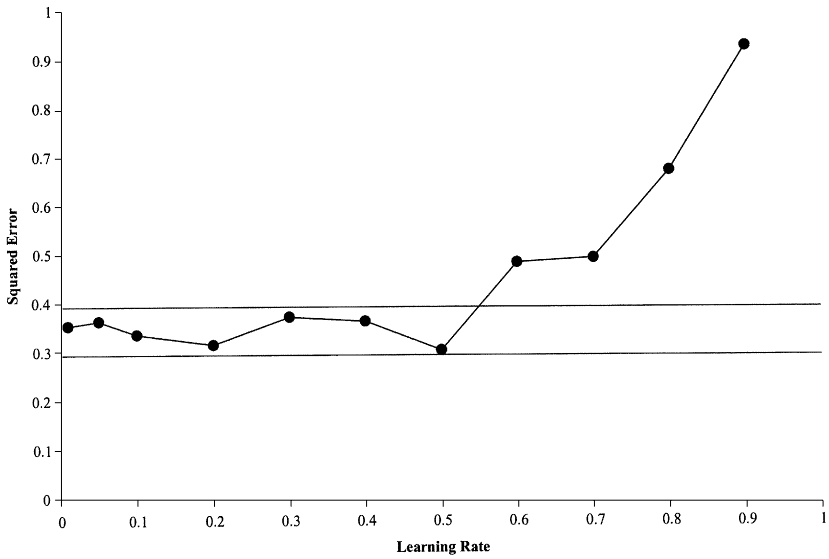

Fig. 7. Variation of squared error value for various Kohonen learning rates.

is at the least distance from an ideal point. The aim is to obtain a solution that is as ‘close’ as possible to some ideal solution. The distance measure used in CP is of the family of L_p-metrics and given as

$$L_p(a) = \left[\sum_{j=1}^{J} w_j^p \left| \frac{f_j^* - f(a)}{M_j - m_j} \right|^p \right]^{1/p}, \tag{21}$$

where $L_p(a)$ is the L_p-metric for alternative a, $f(a)$ the value of criterion j for alternative a, M_j the maximum (ideal) value of criterion j in set A, m_j the minimum (anti ideal) value of criterion j in set A, f_j^* the ideal value of criterion j, w_j the weight of the criterion j, and p the parameter reflecting the attitude of the decision maker with respect to compensation between deviations. For $p = 1$, all deviations from f_j^* are taken into account in direct proportion to their magnitudes, meaning that there is full (weighted) compensation between deviations. For $2 \leqslant p \leqslant \infty$, the largest deviation has the greatest influence, so that

Table 5
Ranking pattern of irrigation planning strategies for various values of p in CP

Group number	L_p metric value for $p = 1$	Rank	L_p metric value for $p = 2$	Rank	L_p metric value for $p = \infty$	Rank
S1	0.4119	1	0.2426	1	0.1743	1
S2	0.5756	4	0.3849	4	0.2911	2
S3	0.6247	5	0.4405	5	0.3358	5
S4	0.5364	3	0.3605	3	0.3059	3
S5	0.4465	2	0.3299	2	0.3149	4

compensation is only partial (larger deviations are penalised). For $p = \infty$, the largest deviation is the only one taken into account (min–max criterion) corresponding to zero compensation between deviations (perfect equity).

Comprom, a decision support system for CP, has been developed to analyse the reduced payoff matrix (indicated with asterisk in Table 2). In *Comprom*, number of alternatives, criteria, payoff matrix (alternatives versus criteria array) and weights of criteria are to be given as inputs by the user. User is having the flexibility to process any number of alternatives and criteria. Values in the payoff matrix and weights can be changed at any stage. The value of parameter 'p' can also be changed, to study the sensitivity of the ranking pattern. Comprom computes L_p-metric values for each alternative. Minimum L_p-metric value is taken as the best and accordingly a ranking pattern is obtained for all alternatives. Ideal and anti-ideal values for CP are obtained from Table 1 (upper and lower bounds). Irrigation planning strategy with the minimum L_p-metric value is selected as the compromise solution. Table 5 presents L_p-metric values and corresponding ranking pattern for each irrigation planning strategy for three values of $p = 1, 2, \infty$. For all the three values of $p = 1, 2, \infty$, irrigation planning strategy S1 is ranked as the best, having low L_p-metric values of 0.4119, 0.2426 and 0.1743, respectively.

Sensitivity analysis is performed, to check the effect of various parameters on the ranking patterns. In CP, various values of $p = 1, 2, \infty$, while analysing the ideal and anti-ideal values (from Table 2) for each criterion, are considered. It is observed from above sensitivity analysis that top position of S1 remains unchanged.

It is concluded from the above analysis and the observed sensitivity of the parameters that irrigation planning strategy S1 can be analysed for further evaluation. Table 1 presents the derived parameters corresponding to the best compromise irrigation strategy, S1. Figs. 3–5 present cropping plans for regions PLBC, PRBC and MRBC, for the best compromise irrigation strategy, S1 (as obtained by CP). It is also observed from the present study, that the above four phase methodology is effective for the multiobjective irrigation planning problem presented and can be extended to similar situations where number of strategies are large in number.

3. Conclusions

In the present paper, four-phase methodology is employed, to select the best compromise irrigation planning strategy, in a multi objective context for the case study of Jayakwadi irrigation project, Maharashtra, India with integration of Kohonen neural networks and Multicriterion Analysis. The following conclusions emanated from the study:

1. It is observed that the four-phase methodology employed is effective for multiobjective irrigation planning problems and can be extended to similar situations.
2. The potential of Kohonen Neural Networks, as a classification tool, is utilised in the present analysis and found to be useful for classifying nondominated irrigation planning strategies effectively.
3. Nineteen strategies are grouped into five groups using KNN methodology. Irrigation planning strategies from each group are selected, based on minimum squared dispersion value criterion.
4. It is observed from CP analysis that irrigation planning strategy S1 is ranked as the best, having the lowest L_p-metric values.
5. Effect of learning rate is significant on the squared deviation. This is more so when learning rate is greater than 0.6, indicating the necessity for careful selection of the learning rate.

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