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Modeling Evaporation-Seepage Losses for Reservoir Water Balance in Semi-arid Regions

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Abstract In the water balance of reservoir system, evaporation plays a crucial role particularly so for the reservoir systems of smaller size located in the semi-arid or arid regions. Such regions are most often characterized by significant seepage losses from reservoirs, besides evaporation losses. Usually, in the optimization of a reservoir system, it is a common practice to assume evaporation loss either as some constant value or as negligible. Such assumptions, however, may affect the results of reservoir optimization. This is demonstrated in this study by a case study in the optimal scheduling of Pilavakkal reservoir system in Vaipar basin of Tamilnadu, India. For modeling reservoir losses, many models are available, of which, Penman combination model is most commonly used. In this study, an alternative approach based on Genetic Programming (GP) is proposed. The results of GP and Penman model for both evaporation loss estimation and reservoir scheduling are compared. It is found that while GP and Penman combination model performs equally well for estimating evaporation losses, GP is also able to model seepage losses (or other losses from reservoir) to a much better degree. It is also shown the reservoir scheduling does get influenced based on how the reservoir losses are modeled in the reservoir water balance equation.

Keywords Evaporation losses · Seepage losses · Reservoir scheduling · Genetic programming · Penman combination equation

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1 Introduction

In the water balance of reservoir system, evaporation plays a crucial role particularly so for the reservoir systems of smaller size located in the semi-arid or arid regions (Kenabatho and Parida 2005). Due to differences in the heating and cooling of water bodies, evaporation from small shallow reservoirs is usually considered to be quite different from that of large and deep reservoirs (Subramanya 2006). This is further enhanced in case of smaller reservoir located in a semi arid region due to hot dry air moving from land surface. Besides, in many cases, seepage losses from reservoirs also contribute significantly (Harboe et al. 1994; Wegner 1999). Thus, any attempt towards optimal design of reservoir capacity or release from reservoirs should account for these losses appropriately. Lack of proper consideration may lead to err on the side of greater risk, as reported by Hugo (2002).

Most of the reservoir operation studies reported in the literature do not explicitly model the reservoir losses. For example, Harboe et al. (1994) adopted mean monthly evaporation rate and a pre-defined relationship of seepage as a function of reservoir storage level in the reservoir water balance equation. Shiau and Lee (2005) assumed the reservoir losses to be negligible in their water balance equation, however, they included the reservoir spill. Ganji et al. (2008) used only the evaporation loss term in the water balance equation. However, the detail of how it is estimated is not provided. Sun et al. (1996), however, in their work has used a generalized network formulation to incorporate the non-linear evaporation loss function of a reservoir in their water supply optimization model.

The present study intends to model the evaporation and seepages losses from the reservoir and study the effect of such modeling in the end result obtained from optimal reservoir scheduling. Many methods are reported in the estimation of evaporation losses from free water surfaces, which can be grouped into several categories, including: empirical methods (e.g. Kohler et al. 1955), water budget methods (e.g. Guitjens 1982), energy budget methods (e.g. Fritschen 1966), mass transfer methods (e.g. Harbeck 1962); and combination methods (e.g. Penman 1948). Of these, the Penman combination equation is the most commonly used. For instance, Sadek et al. (1997) compared Penman and other methods to estimate evaporation loss from High Aswan Dam in Egypt. Mosner and Aulenbach (2003) compared four different methods for estimating lake evaporation and concluded that Penman model underestimates by 1.1 in. during study period. Makdessi et al. (2005) observed that the use of semi-empirical equations to approximate the radiation terms in the Penman Method will cause the standard Penman method to underestimate evaporation a little over 2% compared to estimates using real radiation data. Recently, Tanny et al. (2008) did an elaborative study in northern Israel comparing Penman combination model with the measured evaporation loss from small water bodies and concluded that Penman–Monteith–Unsworth and Penman–Brutsaert models that used elaborative wind functions performed better than models with simplified wind functions or a constant wind contribution.

Though literatures cover application of many methods in estimation of evaporation from water bodies, estimation of other losses besides evaporation losses (such as seepage losses) are not explicitly dealt with. Since Penman combination models are developed for estimating evaporation or evapotranspiration losses, they do not provide any information on seepage or other losses from the reservoirs, the knowledge of which plays a very crucial role when it comes to reservoir scheduling. Therefore, in this study, Darwinian based evolutionary algorithm, genetic programming (GP) technique is proposed as a potential alternative technique. As observed by Sudheer et al. (2002), though there is a growing interest in the recent times in the modeling of non-linear relationships with development of variety of test procedures for detecting the non-linearities, yet for many applications theory does not guide the model-building process in terms of arriving at choosing relevant variable or functional form. Towards this end GP seems to be a very potential technique. The advantage of this algorithm lies in the fact that from a given set of climatological and/or other parameters believed to affect the process of evaporation and seepage, GP selects the most suitable parameters, and thus by suitable intuitive analysis and necessary data, empirical mathematical models most suited to the system under consideration can be easily evolved.

The potential of GP in hydrological applications have been demonstrated by many researchers in the recent past. For example, Khu et al. (2001) used GP as an error updating scheme to complement Mike 11 model to show that the proposed method predicts the runoff very accurately. Sivapragasam et al. (2006) applied GP to river routing problem to show that non-linear Muskingam model must include one more intermediate storage term to explain the routing process adequately. GP was able to evolve this term for the study area. Parasuraman et al. (2007) applied GP for modeling evapotranspiration process and the compared their results with those obtained from ANN and Penman–Monteith (PM) model. It was seen that both ANN and GP performs better than PM model, while their individual performances are not very different. But, the advantage with GP is that the most significant parameter influencing the model could be clearly identified.

The present work differs from the previous studies in three major ways viz., (1) based on the historical measured records, a single mathematical model for estimation of evaporation and seepage losses from a reservoir is developed.; (2) the model developed is not merely a determination of unknown coefficients values of one of the widely used empirical equations (through appropriate calibration); rather GP allows developing most meaningful local (or regional) models unique to the reservoir system under consideration; and (3) the mathematical models are directly incorporated in the genetic algorithm (GA) based irrigation water release optimization model of the reservoir systems in order to study the impact of evaporation and seepage losses in the optimal scheduling of the reservoirs.

2 Study Area Description

Pilavakkal reservoir system consisting of Periyar and Kovilar reservoirs in Virudhunagar District of Tamilnadu State, India is considered in this study. These two reservoirs lie in the upper part of the Vaippar basin, separated 5 km apart and located at (9°41′N, 77°23′E) and (9°38′N, 77°32′E) respectively. Periyar and Kovilar dams are earthen dams and are provided with river sluices and canal sluices to feed the downstream command area. These reservoirs are constructed across the two non-perennial Periyar and Kovilar rivers, which carry only intermittent flash flows

Table 1 Hydraulic particulars of the reservoirs

S. No	Characteristics	Periyar	Kovilar
1	Catchment area (km^2)	45.30	24.77
2	Length of reservoir (m)	900	660
3	Full reservoir level(m)	204.50	212.00
4	Crest level of spill way (m)	199.93	208.94
5	Capacity at crest level of spillway (Mm^3)	2.35	1.89
6	Maximum flood discharge (cumec)	286	220.8
7	Capacity at FRL (Mm^3)	5.43	3.76
8	River bed level (m)	187.59	195.98

depending on the seasonal rainfall. Kovilar reservoir has a larger surface area with relatively shallow water depth when compared to Periyar reservoir. There are no meteorological stations available within the command area of Pilavakkal irrigation system. But there is one station maintained by the ground water wing of the state public works department located approximately at a distance of 20 km from the Pilavakkal system command at Kavalur. This meteorological station represents the whole of Vaippar basin. Historical fortnightly records of several hydro meteorological variables, including temperature, wind speed and relative humidity are obtained for a period of 1992 to 2000 from this meteorological station. The hydraulic particular of the reservoirs as obtained from the Public Works Department (PWD) is given in Table 1.

The command area experiences a tropical climate throughout the year. A maximum mean monthly temperature of 38.34°C is observed during May, whereas a minimum mean monthly temperature of 20.04°C occurred in the month of January. Mean annual rain fall of the dam site is 1,187 mm against the state average of 945mm. However, the rainfall is highly erratic and is less than 75% of the mean in 20% of the years. Hence the area is classified as drought prone according to the standards fixed by the Indian Meteorological Department. The reservoirs are constructed with the aim to directly irrigate the canal command (new command) and support irrigation of tank command (old command) of the 40 downstream tanks. The reservoir scheduling is to be done for two crop (primarily paddy) seasons in a year. A total of 3,125.18 ha is realized during the long term crop season for the old command as against 532.18 ha for the new command. The short term paddy is realized over an area of 683.75 ha for the old command.

3 Genetic Programming

Genetic programming (GP) is an evolutionary algorithm to approximate the equation, in symbolic form, that best describes how the output relates to the input variables. GP works by imitating aspects of natural evolution to generate a solution that maximizes (or minimizes) some fitness function (Koza 1992). The algorithm considers an initial population of randomly generated programs (equations), derived from the random combination of input variables, random numbers and functions which include arithmetic operators (+, −, ×, ÷), mathematical functions (sin, cos, exp, log), logican/comparison functions etc, which has to be appropriately chosen based on some understanding of the process. Typically the population of a genetic programming process contains a few hundred individuals and evolves through the action of evolutionary operators known as crossover, mutation and selection. The programs that best fit are selected to exchange part of the information between them to produce better programs through evolutionary operators which mimic the natural world reproduction process. Exchanging the parts of best programs with each other is called crossover and randomly changing programs to create new programs is called mutation. A population of solution candidates evolves through many generations towards a solution using certain evolutionary operators and a 'survival-of-the fittest' selection scheme. Selection involves evaluating the fitness of each population member and choosing the fittest to continue to the next generation; there are various selection strategies which can be used to determine which of the population members will survive to the next generation (Koza 1992). The programs which less fitted the data are discarded. This evolution process is repeated over successive generations and is driven towards finding symbolic expressions describing the data, which can be scientifically interpreted to derive knowledge about the process. Details on GP can be obtained from (Koza 1992; Babovic and Keijzer 2000; Khu et al. 2001; Sivapragasam et al. 2006). In this study, the Discipulus (1998) software used for implementing GP.

4 Model Development

The evaporation-seepage estimation models for Periyar and Kovilar reservoirs are constructed based on the historically available meteorological data as well as the real time changes in the reservoir water level. The analysis is carried out for a fortnightly time period of operation. Meteorological parameters will primarily address the evaporation process. In addition, surface area of the reservoir at a given depth of reservoir storage (a derived parameter) is also considered for evaporation modeling. This surface area is a representative surface area obtained by dividing storage volume of the reservoir by the depth of reservoir storage. For seepage, due to lack of information on parameters such as the soil moisture (saturation) condition, the permeability, any geological formations such as cracks etc which affects seepage directly, the only parameter which is considered in model development is the depth of reservoir storage. Now, for a given crop season, say between October and January, in order to derive optimal irrigable area and corresponding reservoir scheduling, the forecasted information on inflow to reservoirs and the expected evaporation-seepage losses from the reservoirs during the crop period are necessary. Since, it is difficult to predict each individual meteorological parameter for the entire crop season, an assumption is made in this study (after careful analysis of the climatic conditions of the catchment) that the average climatic condition during a particular time period in the current year may not be very different from the preceding year's climatic conditions, unless the basin undergoes some drastic natural or man made changes (which is found to be absent in this basin). Thus, the average climatic condition during the first fortnight of November 2005 (say) may not very much differ from that of November 2004. As such, the meteorological parameters observed during November 2004 can be taken as representative parameters for November 2005. With this assumption, the parameters considered for model development can be expressed in the functional form as below:

$$E_t = f\,(h_{t-1}, \mathrm{SA}_{t-1}, T_{t-24}, \mathrm{RH}_{t-24}, N_{t-24}, V_{t-24}) \tag{1}$$

where

E_t	evaporation losses at time t (Mm^3)
$T_{(t-24)}$	temperature at the same fortnight 1 year before (in °C)
$V_{(t-24)}$	wind velocity at the same fortnight 1 year before (in kmph)
$N_{(t-24)}$	sunshine hour at the same fortnight 1 year before (in hours/day)
$\mathrm{RH}_{(t-24)}$	relative humidity at the same fortnight 1 year before t (in %)
$\mathrm{SA}_{(t-1)}$	surface area of reservoir one fortnight before (in m^2)
$h_{(t-1)}$	reservoir storage depth one fortnight before (in m)

It should be noted that inflow to reservoirs is not considered as one of the components in the GP input because it is assumed that reservoir storage depth accounts for inflows.

Selection of functions needs the knowledge about the process. Generally seepage loss variations are assumed to be parabolic in nature (as is usually done in studies involving seepage through levees), however, in practice, this may not be strictly true. In order to account this, 'exponential' term is also included as one of the GP functions together with sine and cosine functions. Evaporation losses are some non-linear combinations of input parameters. Accordingly, the final set of GP functions are considered in the model development are Addition, Multiplication, Subtraction, Exponential and Trigonometric.

The GP variables are range standardized and GP is run to obtain the required models. The following models are obtained for Periyar and Kovilar reservoirs.

4.1 Evaporation-Seepage Model for Periyar Reservoir

For Periyar reservoir, the GP obtained evaporation-seepage loss model is given by Eq. 2

$$E_t = \frac{0.081 h_{t-1}^3 T_{t-24}^4 V_{t-24}}{(\mathrm{RH}_{t-24})^4 \, (N_{t-24})^2} \tag{2}$$

As observed from Eq. 2, it is clear that the process of evaporation is mainly affected by wind velocity (as the normalized velocity term is of degree one). This is evident as Periyar reservoir is found to be not surrounded by forests and thus permitting free circulation of winds over the water surface. Further, the surface area is not found to affect the process. However, it can be noted that the presence of depth term actually indirectly accounts for surface area term because of linear relationship between the two variables. Thus, the effect of surface area, heat storage, inflow and seepage can be considered lumped in the depth term. Table 2 shows the comparison of actual evaporation-seepage losses and that obtained by Eq. 2. The same is also plotted as a scatter plot in Fig. 1.

Table 2 Comparison of actual and predicted evaporation-seepage loss: Periyar

S. No	Month	Evaporation and seepage losses (Mm^3)		
		Actual	Predicted (GP)	Predicted (Penman)
1	Mar.2000, 1–15	0.004	0.036	0.048
2	Mar.2000, 16–31	0.122	0.080	0.050
3	Apr.2000, 1–15	0.286	0.173	0.044
4	Apr.2000, 16–30	0.437	0.159	0.043
5	May.2000, 1–15	0.413	0.115	0.051
6	May.2000, 16–31	0.094	0.101	0.038
7	Jun.2000, 1–15	0.052	0.043	0.025
8	Jun.2000, 16–30	0.059	0.021	0.024
9	July.2000, 1–15	0.091	0.071	0.025
10	July.2000, 16–31	0.104	0.067	0.024
11	Aug.2000, 1–15	0.098	0.026	0.021
12	Aug.2000, 16–31	0.029	0.023	0.023
13	Sep.2000, 1–15	0.032	0.035	0.017
14	Sep.2000, 16–30	0.010	0.046	0.017
15	Oct.2000, 1–15	0.038	0.023	0.027
16	Oct.2000, 16–31	0.036	0.048	0.021
17	Nov.2000, 1–15	0.052	0.014	0.008
18	Nov.2000, 16–30	0.020	0.002	0.007
19	Dec.2000, 1–15	0.004	0.004	0.016
20	Dec.2000, 16–31	0.036	0.018	0.012

4.2 Evaporation-Seepage Model for Kovilar Reservoir

For Kovilar reservoir, the GP obtained evaporation-seepage loss model is given by Eq. 3:

$$\begin{aligned} E_t = 0.03 &\left[\mathrm{SA}_{t-1}\left(\mathrm{SA}_{t-1} - 2h_{t-1}\right) + \mathrm{RH}_{t-24}\left(\mathrm{RH}_{t-24} - 2h_{t-1}\right)\right] + h_{t-1} N_{t-24} \\ &\times \left[0.2\left(h_{t-1}^2 + \mathrm{SA}_{t-1}^2 + 0.5\mathrm{RH}_{t-24}^2\right) + 0.1 h_{t-1}\mathrm{RH}_{t-24} - 0.51 h_{t-1} \right. \\ &\left. + 0.18\mathrm{SA}_{t-1} + 0.07\right] V_{t-24} \end{aligned} \quad (3)$$

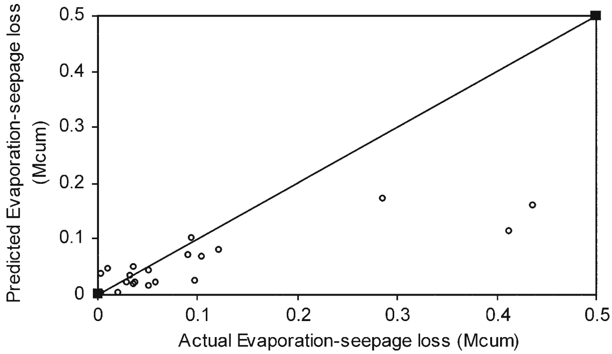


Fig. 1 A scatter plot showing actual and predicted evaporation-seepage losses (Periya Reservoir)

Table 3 Comparison of actual and predicted evaporation–seepage loss: Kovilar

S. No	Month	Evaporation and Seepage Losses(Mm^3)		
		Actual	Predicted (GP)	Predicted (Penman)
1	Mar.2000, 1–15	0.024	0.014	0.019
2	Mar.2000, 16–31	0.139	0.073	0.018
3	Apr.2000, 1–15	0.120	0.058	0.016
4	Apr.2000, 16–30	0.141	0.058	0.014
5	May.2000, 1–15	0.104	0.051	0.013
6	May.2000, 16–31	0.030	0.027	0.012
7	Jun.2000, 1–15	0.002	0.014	0.006
8	Jun.2000, 16–30	0.021	0.013	0.006
9	July.2000, 1–15	0.054	0.018	0.006
10	July.2000, 16–31	0.067	0.018	0.005
11	Aug.2000, 1–15	0.002	0.013	0.004
12	Aug.2000, 16–31	0.013	0.012	0.005
13	Sep.2000, 1–15	0.018	0.014	0.005
14	Sep.2000, 16–30	0.007	0.014	0.004
15	Oct.2000, 1–15	0.006	0.009	0.013
16	Oct.2000, 16–31	0.000	0.008	0.008
17	Nov.2000, 1–15	0.013	0.008	0.004
18	Nov.2000, 16–30	0.006	0.008	0.004
19	Dec.2000, 1–15	0.001	0.013	0.006
20	Dec.2000, 16–31	0.002	0.011	0.004

Neglecting the fifth order terms, the equation can be simplified to

$$E_t = 0.03\left[\mathrm{SA}_{t-1}\left(\mathrm{SA}_{t-1} - 2h_{t-1}\right) + \mathrm{RH}_{t-24}\left(\mathrm{RH}_{t-24} - 2h_{t-1}\right)\right] \\ + \left[0.18\mathrm{SA}_{t-1} - 0.51h_{t-1} + 0.07\right] h_{t-1} N_{t-24} V_{t-24} \quad (4)$$

Here, the temperature and sunshine hours are found to be comparatively less effective in determining the evaporation-seepage losses as this reservoir is covered with relatively dense forest area making the sunlight to difficult to reach effectively. The predominant factor is again the velocity of wind. Table 3 compares the prediction values and Fig. 2 shows the scatter plot.

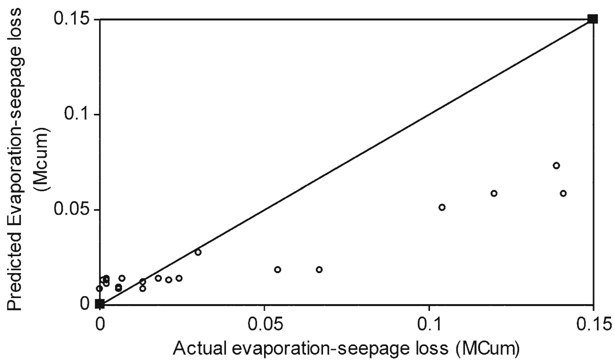


Fig. 2 A scatter plot showing actual and predicted evaporation-seepage losses (Kovilar Reservoir)

4.3 Evaporation Loss Estimation by Penman Combination Model

The fortnightly meteorological information, the following form of Penman combination equation (Subramanya 2006) was applied:

$$E = \frac{AH_n + E_a\gamma}{A + \gamma} \tag{5}$$

where E = daily evapotraspiration in mm per day

- A slope of the saturation vapour pressure Vs temperature at the mean air temperature
- H_n net radiation in mm of evaporable water per day
- E_a parameter including wind velocity and saturation deficit
- γ psychrometric constant = 0.49 mm of Hg/°C

The net radiation is estimated by the following equation:

$$H_n = H_a\left(1 - r\right)\left(a + b\,\frac{n}{N}\right) - \sigma T_a^4\left(0.56 - 0.092\sqrt{e_a}\right)\left(0.10 + 0.90\frac{n}{N}\right) \tag{6}$$

- H_a incident solar radiation outside the atmosphere on a horizontal surface (a function of latitude)
- a constant depending upon the latitude ϕ and is given by $a = 0.29\cos\phi$
- b a constant (assumed here as 0.52)
- n actual duration of bright sunshine in hours
- N maximum possible hours of bright sunshine (it's a function of latitude)
- r albedo. Here r is assumed as 0.05 (for water surface)
- σ Stefan–Boltzman constant
- T_a mean air temperature in degrees Kelvin
- e_a actual mean vapour pressure in the air in mm of Hg

The parameter E_a is estimated as

$$E_a = 0.35\left(1 + \frac{u_2}{160}\right)(e_w - e_a) \tag{7}$$

in which,

- u_2 mean wind speed at 2 m above ground in km/day
- e_w saturation vapour pressure at mean air temperature in mm of Hg
- e_a actual vapour pressure, as already defined.

This equation is used with $r = 0.05$ for estimating evaporation from a water surface. The results from this model are also appended with GP results in Tables 1 and 2 for Periyar and Kovilar reservoir respectively.

4.4 Discussion on Prediction by GP and Penman Combination Model

For Periyar reservoir, GP prediction is much better than that from Penman combination equation for the months of March to July. For the rest of the months, both the models perform almost equally well. The correlation coefficient is found to be 0.85 and 0.64 for GP and Penman model respectively (Table 2).

For Kovilar reservoir, again similar pattern in the prediction is seen with a correlation coefficient of 0.95 and 0.65 for GP and Penman model respectively. The prediction by GP for the month of March to July is better than that obtained by Penman, though the values of prediction itself is not good (Table 3).

From the predictions by GP and Penman model, the following observations are made:

(a) The GP and Penman predictions during months of August to December is almost similar, while GP results are found to be better during the months March to July This means there are some other losses in the reservoir which is more prominent (of which seepage being the primary one) besides evaporation during these months, and which Penman combination equation cannot adequately model for the obvious reason that it is developed only to model evaporation or evapotranspiration losses.

(b) In an overall sense, the predictions are not satisfactory. This is primarily because the meteorological data are fortnightly average, and the location of the meteorological station, though only 20 km away physically, is not fully representative of the reservoir site. Usually, fortnightly, monthly or yearly estimation of evaporation using Penman combination model is done by summing up the hourly or daily predictions. That is expected to give better estimates than when found using mean monthly or fortnightly values. This is one probable reason for not so good prediction by both GP and Penman models, in general.

(c) Although it is difficult to partition clearly the components of evaporation and seepage from the GP evolved mathematical models, yet some insight can be obtained as to which parameter(s) among the input variables most prominently influence the phenomenon. Care can be taken to ensure that those parameters are measured with higher precision.

The predictions from GP and Penman combination models are integrated with the reservoir water balance equation to derive the reservoir scheduling. This is discussed in the next section.

5 Derivation of Optimal Reservoir Scheduling

Genetic algorithm (GA) is chosen for finding optimal scheduling of the reservoir system. It is desired to find out the maximum irrigable area (old and new command inclusive) for a given crop season (with initial storage conditions and forecasted information) and the fortnightly scheduling details for the tanks as well as reservoirs. Further, a target storage is desired at the end of the current crop season in order to ensure necessary initial storage for the next crop season in the event of monsoon failure. Accordingly, the objective function is formulated as the dual objectives of maximizing the irrigable area and minimizing target storage deficit as below:

$$\text{Max } Z = \left[\left(\frac{\sum_{i=1}^{c} A_i}{A} \right) - \alpha_1 \left(\frac{(\text{PS}_n + \text{KS}_n) - T_s}{(\text{PS}_{\max} + \text{KS}_{\max}) - T_s} \right)^2 \right] \tag{8}$$

where A_i = Minimum area that can be irrigated for cluster i for the given input conditions; c = number of clusters; PS_n = storage in Periyar at the end of the operating time horizon, KS_n = storage in Kovilar at the end of the operating time horizon, T_s = combined target storage, n = operating time horizon (depending on the long-term or short-term season), PS_{max} = maximum storage of Periyar reservoir, KS_{max} = maximum storage of Kovilar reservoir, α_1 = penalty coefficient.

In order to solve the above optimization problem using GA, chromosome has to be constructed for the variables. A chromosome is a potential solution and is comprised of a series of substrings or genes, representing components or variables that either form or can be used to evaluate the objective function of the problem (Wardlaw and Sharif 1999). There are a total of 96 decision variables (for long term operation) or 72 decision variables (for short term). The 96 variables for long term operation consist of reservoir releases for eight time step (16 variables); tank cluster releases for eight time steps (32 variables); the percentage of total release from the two reservoirs which are to be distributed to four tank clusters and Periyar and Kovilar canal command (48 variables). Each of these variables are considered as a gene, and they are real coded in the GA. It can be noted that traditionally GAs have used binary coding in which a chromosome is represented by a string of binary bits that can encode integers, real numbers or anything else appropriate to the problem. However, the problem with such coding is in large jumps in variable values between different generations which leads to difficulty in convergence to a good solution. Real coded chromosomes are used with success by many researchers, wherein individual genes of a chromosome are initially allocated values randomly within the feasible limits of the variable represented. This type of coding offers a significant advantage in saving of computer time on decoding for objective function evaluation. More details can be found in Wardlaw and Sharif (1999).

In many practical problems, GA results are found to be sensitive to crossover and mutation probabilities (Wardlaw and Sharif 1999). This is because genetic material lost at the start of a run, through either crossover or mutation, may be needed to improve fitness in the later stages of a run. To decide upon the optimal GA parameters, the trial-and-error method suggested by Wardlaw and Sharif (1999) is followed. For a population size of 500, cross-over probability is varied in the range 0.8–0.95 with an increment of 0.5. For each cross-over probability, mutation probability is varied in the range 0.1–0.4%. The results are shown in Fig. 3. The

Fig. 3 Determination of optimal crossover and mutation values

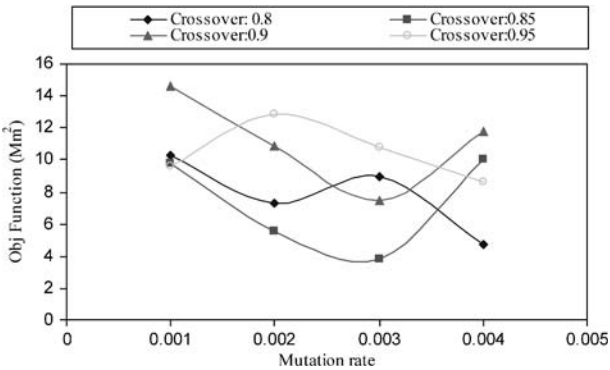


Table 4 Total irrigable area under each cluster after optimization

Maximal area cultivated for different conditions of evaporation/seepage	Cluster no.						
	C1 (Mm^2)	C2 (Mm^2)	C3 (Mm^2)	C4 (Mm^2)	C5(Mm^2)	C6 (Mm^2)	Total (Mm^2)
Actual	1.05	1.25	4.52	3.36	0.23	0	10.43
GP model	1.69	1.33	3.83	3.28	0.45	0.10	10.71
Penman combination	1.40	2.73	4.23	4.91	0.08	0.05	13.41
Constant values	0.99	1.36	5.90	2.58	0.09	0.54	11.46
Losses neglected	1.07	0.67	5.56	5.12	1.40	0.28	14.12

following optimal values are arrived at: crossover rate – 0.9, mutation rate – 0.001, and number of population – 500.

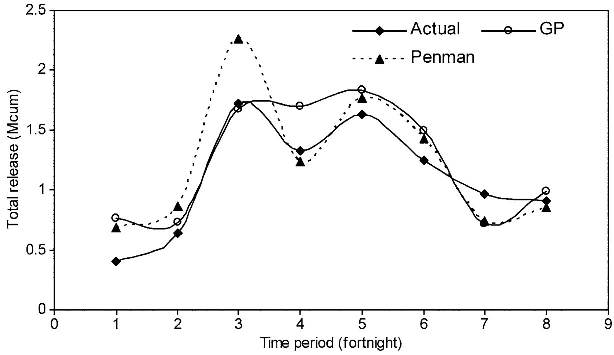
The optimization is demonstrated for long term crop season with initial storage in reservoirs as 1.54 and 0.136 Mm^3. The tank storages are assumed as 30% of their capacity. The inflow for the period March 2000 to June 2000 is considered. GP based evaporation-seepage models and the Penman combination models developed above for the Periyar and Kovilar reservoirs are coupled with the GA optimization. Optimization results with actual evaporation-seepage losses are compared with those against GP and Penman forecasted evaporation-seepage model.

The results are compared in Table 4. The old command area is classified into four clusters based on the degree of drought effect, namely C1, C2, C3 and C4. The canal commands for Periyar and Kovilar reservoirs are represented as C5 and C6. Table 4 shows the total area irrigable under each cluster after GA optimization for five situations, namely (a) when actual evaporation/seepage loss is used, (b) when GP derived evaporation/seepage loss is used, (c) when Penman combination equation is used, (d) when evaporation seepage loss is assumed constant as 0.03 and 0.008 Mm^3 for Periyar and Kovilar reservoir respectively and (e) when the evaporation/seepage losses are neglected.

As seen from the table, the total area obtained with actual losses and GP forecasted losses are not much different. Though there is some variation in their distribution in different clusters, such variations are not very significant except for C1. By using the Penman combination model, the maximal irrigable area is found to be 13.41 Mm^2 as against 10.43 Mm^2 from actual losses. This increase can be attributed the fact that Penman equation underestimated the losses for each of the time period. By neglecting the losses completely, the maximal irrigable area is found to be 14.12 Mm^2 which is logically meaningful because there is more water for irrigation.

Figure 4 shows plot of the sum total of water released to all the clusters obtained by optimizing the system with actual and forecasted evaporation-seepage losses respectively. As seen from the figure, the GP based releases are more close to the actual profile when compared with Penman combination models. This shows that the predictions obtained from GP model for evaporation-seepage losses is reliable for use in optimization process.

Fig. 4 Plot showing sum total of water released to all the clusters



6 Conclusion

The following noteworthy conclusions can be arrived at based on the present research study:

(a) When only evaporation losses are to be modeled, there is not much difference in the prediction by GP model or Penman combination equation. However, when other losses are expected to be more, GP model clearly shows better performance.
(b) Though there is not clear cut partition between evaporation and seepage in the models evolved by GP, yet GP does offer some insight into the variables which more significantly influence the reservoir losses. Accordingly, those losses can be measured with higher precision. Wind velocity is found to be the most important meteorological parameter affecting the evaporation process.
(c) The quality and quantity of data very much decides the end results obtained from GP.
(d) As far as reservoir scheduling is concerned, the results are found to vary depending upon how the evaporation/seepage phenomena are modeled. Even though the present case study consisted of a complex system of two reservoir and 40 downstream tanks, yet the evaporation/seepage losses from the reservoirs do affect the optimization results. The difference could be more pronounced had the reservoir system been less complex. Hence care should be observed to model these losses appropriately. Further studies on this are recommended to come to arrive at more clear understanding.

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