CHAPTER 5

OPTIMIZATION OF RESERVOIR OPERATIONS

5.1 GENERAL

Systems analysis, which involves use of optimization, simulation, and other decision-making techniques, is a set of powerful tools to solve reservoir operation problems. In this chapter, the Genetic Algorithm (GA) technique is applied to the specific case of Pilavakkal reservoir scheme to propose an optimal real-time joint operation policy for the two existing reservoirs. The inputs to the model are inflow, demand and initial storage and the output is the release from the reservoir which needs to be optimized. The effect of choice of inflow horizon on the predicted values of inflow and its impact on the release are demonstrated. The primary objective of forecasting is to reduce the risk in decision making. However the accuracy of predictions decreases with time span of prediction.

Reservoir system operations are complex and generally offer substantial benefits by relatively small improvements in operating efficiency. The function of optimization models is to produce “Optimal results” for complex systems, so it would seem that applying optimization models to multiple reservoir systems would be a perfect match (Otto J Helweg et al 1982). This chapter starts with the formulation of the optimization problem and is applied to the case of Pilavakkal reservoir scheme for various combinations of inflow values to generate scenarios showing the effects of various input variables on the effectiveness of optimization. The optimization
is performed using GA and linear programming tools namely GeneHunter and LINDO.

5.2 RESERVOIR OPERATION MODEL

GA is used to optimize the reservoir operations by minimizing the demand deficit and storage deficit at the end of each time step. The objective function can be written as

\[
\text{Minimise } Z = \sum_{i=1}^{n} \left( (PR_i + KR_i) - D_i \right)^2 + \left( (PS_n + KS_n) - T_s \right)^2 \tag{5.1}
\]

where \( PR_i \) = Periyar Reservoir Release for \( i^{th} \) time step, \( KR_i \) = Kovilar Reservoir Release for \( i^{th} \) time step, \( PS_n \) = Periyar Reservoir Storage at the end of \( n^{th} \) time step, \( KS_n \) = Kovilar Reservoir Storage at the end of the \( n^{th} \) time step, \( D_i \) = Demand (combined), \( T_s \) = Combined target storage at the end of \( n^{th} \) time step. The target storage is the minimum storage required for the reservoirs and was arrived at from site specific considerations of salvaging the crop in the absence of inflow in the subsequent time steps. The value of target storage \( (T_s) \) is taken as 1.1 Mm³. The objective function is subjected to the following constraints.

5.2.1 Continuity equation

\[
PS_{i+1} = PS_i + PI_{i+1} - PR_{i+1} \tag{5.2}
\]

If \( PS_{i+1} > 2.35 \), Then

\[
PS_{i+1} = 2.35
\]

\[
PSP_{i+1} = PS_{i+1} - 2.35 \tag{5.3}
\]

\[
KS_{i+1} = KS_i + KI_{i+1} - KR_{i+1} \tag{5.4}
\]
If $KS_{i+1} > 1.89$ Then

$KS_{i+1} = 1.89$

$Ksp_{i+1} = KS_{i+1} - 1.89$ (5.5)

### 5.2.2 Release constraints

$$PR_i \leq 4 \quad (5.6)$$

$$KR_i \leq 3 \quad (5.7)$$

$$PR_i + KR_i \leq D_i \quad (5.8)$$

Where

$PS_{i+1}$ = Storage in Periyar at $(i+1)^{th}$ time step

$KS_{i+1}$ = Storage in Kovilar at $(i+1)^{th}$ time step

$PS_i, KS_i$ = Storage in Periyar and Kovilar rivers at $i^{th}$ time step

$PI_{i+1}$ = Inflow to Periyar at $(i+1)^{th}$ time step

$PR_{i+1}$ = Release from Periyar at $(i+1)^{th}$ time step

$KR_{i+1}$ = Release from Kovilar at $(i+1)^{th}$ time step

$PR_i, KR_i$ = Release in Periyar and Kovilar rivers at $i^{th}$ time step

$Psp_{i+1}$ = Spill from Periyar reservoir during the $(i+1)$ time step,

$Ksp_{i+1}$ = Spill from Kovilar reservoir during the $(i+1)$ time step

The upper limits for the reservoir releases are fixed based on the capacity of the distribution network. All the storage, release and demand values are in Mm$^3$.

### 5.3 IMPLEMENTATION USING GENETIC ALGORITHM

Genetic algorithms (GA) seek to solve optimization problems using the methods of evolution, specifically survival of the fittest. In a typical
optimization problem, there are a number of variables which control the process, and a formula or algorithm should combine all the variables to fully model the process. The problem is then to find the values of the variables which optimize the model in some way. If the model is a formula, then we will usually be seeking the maximum or minimum value of the formula. There are many mathematical methods which can optimize problems of this nature (and very quickly) for fairly "well behaved" problems. These traditional methods tend to break down when the problem is not so well behaved. Examples of these types of problems include combinatorial problems or problems where the fitness function is not a smooth, continuous mathematical formula. The optimization using GA in our case is achieved through the application of the software GeneHunter (Release 4.2).

GeneHunter solves optimization problems using genetic principles. It will create a population of possible solutions to the problem (individuals). The individuals in the population will carry chromosomes which are the values of variable of the problem. GeneHunter actually solves problem by allowing the less fit individuals in the population to die and selectively breeding the fit individuals. The process is called selection, as in the selection that takes place in a survival of the fittest situation. GeneHunter takes two parent individuals and mate them (Crossover). The offspring of the matted pair will receive some of the characteristics of the mother and some of the father. In nature offspring often have some slight abnormalities called mutation. Usually these mutations are disabling and inhibit the ability of the offspring to survive. But once in a while they improve the fitness of the individual.

GeneHunter occasionally cause mutations to occur. As GeneHunter mates fit individuals and mutates some, the population under goes generation change. The populations will then consist of offspring plus a few of the older
individuals which GeneHunter allows to survive to the next generation. These are the most fit in the population and we will want to keep them breeding. The fit individuals are called elite individuals. After dozens or even hundreds of generations, a population eventually emerges wherein the individuals will solve the problem very well. In fact, the fit (elite) individuals will be an optimum or close to optimum solution. The process of selection, crossover, and mutation are called genetic operators.

In this problem the decision variables namely the reservoir releases are assigned as continuous chromosomes with the hard constraints as given in equations 5.6 and 5.7. The combined releases from both reservoirs for each time step are to be kept below or equal to the demand as in equation 5.8 and is taken care of by the soft constraints in GeneHunter. The optimization is performed with a 16 bit chromosome length and population size of 200. The total number of evolutions decrease with a decrease in population size, and hence desired results may not be achieved with smaller population sizes (Wardlaw and Sharif 1999).

The evolution parameters crossover and mutation probabilities are fixed at 0.8 and 0.01 respectively after extensive trials. Cross over probabilities from 0.5 to 0.95 were considered through the runs with a fixed length of 500 generations by Wardlaw and Sharif (1999). They have mentioned that the optimal cross over probability appears to be 0.8 for grey coding. The mutation probabilities applied were ranging from 0.002-0.208. It is reported that achieving an optimal sequence of 48 bits is quicker than 144 bits for their problem. In the present study, the termination criterion is fixed as best fit unchanged after 75 generations. Srinivasa Raju and Nageshkumar (2004) have also tried with various combinations of crossover and mutation probabilities. They have chosen a population size of 50 and a maximum
number of generations as 200. Termination criterion was set to perform 200 generations.

5.4 TIME HORIZONS

The accuracy of inflow predictions using various techniques have been found to have a bearing on the time horizon and the above effect on the subsequent optimization of reservoir operations were studied with different time horizons. In the fitness function given in equation 5.1, optimization is performed with two different cases with varying input data as listed below.

Case 1 (a) Two time steps (n=2) with actual inflow, storage and demand data as inputs.
(b) Two time steps (n=2) with forecasted inflow using ANN, storage and demand data as inputs.
(c) Two time steps (n=2) with best forecasted inflow using ANN, storage and demand data as inputs.

Case 2 (a) Four time steps (n=4) with actual inflow, storage and demand data as inputs.
(b) Four time steps (n=4) with forecasted inflow using GP, storage and demand data as inputs.
(c) Four time steps (n=4) with best forecasted inflow using GP, storage and demand data as inputs.

5.4.1 Two lead with actual inflow – [Case 1(a)]

The actual fortnightly inflow data for the period August 2001 to December 2002 is shown in Table 5.1. The initial storages for the Periyar and Kovilar reservoirs are 0.441 and 0.091Mm³ respectively. For all the
optimization studies the above time period is considered. In this case to minimize the accumulation of error, the optimum release values (PR$_1$ and KR$_1$) corresponding to the best fit function for the first time step alone is taken and using these release values and the actual inflow during the first time step the initial storage for the next time step is computed. The above process is repeated for the entire irrigation period.

The fitness function values for various generations are shown in figure 5.1. The improvement in the fitness function is evident with increase in number of generations and the best fit was arrived at 124$^{th}$ generation. Srinivasa Raju and Nageshkumar (2004) have reported that, even before reaching 200 generations which was set as termination criteria, the maximum fitness function value was reached at 192$^{nd}$ generation, which was taken as solution, to their problem.

**Table 5.1 Inflow and demand data for Periyar and Kovilar reservoirs**

(Reference: PWD, Virudhunagar District)

<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Month</th>
<th>Periyar Inflow (Mm$^3$)</th>
<th>Kovilar Inflow (Mm$^3$)</th>
<th>Demand (Mm$^3$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Aug 1 – 15, 2001</td>
<td>0</td>
<td>0</td>
<td>1.131</td>
</tr>
<tr>
<td>2</td>
<td>Aug 16 – 31</td>
<td>0</td>
<td>0</td>
<td>1.131</td>
</tr>
<tr>
<td>3</td>
<td>Sep 1 – 15</td>
<td>0.030</td>
<td>0</td>
<td>1.061</td>
</tr>
<tr>
<td>4</td>
<td>Sep 16 – 30</td>
<td>0.444</td>
<td>0.058</td>
<td>0.973</td>
</tr>
<tr>
<td>5</td>
<td>Oct 1 – 15</td>
<td>0.454</td>
<td>0.124</td>
<td>0.439</td>
</tr>
<tr>
<td>6</td>
<td>Oct 16 – 31</td>
<td>2.336</td>
<td>0.749</td>
<td>0.345</td>
</tr>
<tr>
<td>7</td>
<td>Nov 1 – 15</td>
<td>2.600</td>
<td>2.34</td>
<td>3.938</td>
</tr>
<tr>
<td>8</td>
<td>Nov 16 – 30</td>
<td>1.837</td>
<td>1.799</td>
<td>5.488</td>
</tr>
<tr>
<td>9</td>
<td>Dec 1 – 15</td>
<td>0.150</td>
<td>0</td>
<td>3.752</td>
</tr>
<tr>
<td>10</td>
<td>Dec 16 – 31</td>
<td>0.944</td>
<td>0.567</td>
<td>3.752</td>
</tr>
<tr>
<td>11</td>
<td>Jan 1 – 15, 2002</td>
<td>0.375</td>
<td>0.210</td>
<td>4.004</td>
</tr>
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Table 5.1 (Contd…)

<p>| | | | | |</p>
<table>
<thead>
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<th></th>
<th></th>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>12</td>
<td>Jan 16 – 31</td>
<td>0.002</td>
<td>0</td>
<td>3.640</td>
</tr>
<tr>
<td>13</td>
<td>Feb 1 – 15</td>
<td>1.102</td>
<td>0.104</td>
<td>2.909</td>
</tr>
<tr>
<td>14</td>
<td>Feb 16 – 29</td>
<td>0.084</td>
<td>0</td>
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</tr>
<tr>
<td>15</td>
<td>Mar 1 – 15</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>16</td>
<td>Mar 16 – 31</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>17</td>
<td>Apr 1 – 15</td>
<td>0.010</td>
<td>0.014</td>
<td>0</td>
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<tr>
<td>18</td>
<td>Apr 16 – 30</td>
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<td>0</td>
<td>0</td>
</tr>
<tr>
<td>19</td>
<td>May 1 – 15</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>20</td>
<td>May 16 – 31</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>21</td>
<td>Jun 1 – 15</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>22</td>
<td>Jun 16 – 30</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>23</td>
<td>July 1 – 15</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>24</td>
<td>July 16 – 31</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>25</td>
<td>Aug 1 – 15</td>
<td>0</td>
<td>0</td>
<td>1.131</td>
</tr>
<tr>
<td>26</td>
<td>Aug 16 – 30</td>
<td>1.141</td>
<td>0.035</td>
<td>1.131</td>
</tr>
<tr>
<td>27</td>
<td>Sep 1 – 15</td>
<td>0.024</td>
<td>0</td>
<td>1.061</td>
</tr>
<tr>
<td>28</td>
<td>Sep 16 – 30</td>
<td>0</td>
<td>0</td>
<td>0.978</td>
</tr>
<tr>
<td>29</td>
<td>Oct 1 – 15</td>
<td>1.259</td>
<td>0.134</td>
<td>0.439</td>
</tr>
<tr>
<td>30</td>
<td>Oct 16 – 31</td>
<td>1.018</td>
<td>0.207</td>
<td>0.345</td>
</tr>
<tr>
<td>31</td>
<td>Nov 1 – 15</td>
<td>3.151</td>
<td>1.816</td>
<td>3.938</td>
</tr>
<tr>
<td>32</td>
<td>Nov 16 – 30</td>
<td>0.447</td>
<td>0.049</td>
<td>5.488</td>
</tr>
<tr>
<td>33</td>
<td>Dec 1 – 15</td>
<td>0.169</td>
<td>0</td>
<td>3.752</td>
</tr>
<tr>
<td>34</td>
<td>Dec 16 – 31</td>
<td>0.120</td>
<td>0</td>
<td>3.752</td>
</tr>
</tbody>
</table>
The effectiveness of the optimization in terms of demand deficit and target storage is expressed in terms of demand and storage deficit percentages as shown in figure 5.2. The demand is satisfied in the months of peak demand as it coincides with the peak inflows. However, the target storage is not being achieved due to the insufficient inflows during the peak demand periods.
The extent of wastage of water from the system can be measured in terms of the spillage from the reservoirs. In the present study the spill is dealt separately as a constraint. Sometimes it can be incorporated in the continuity equation (Srinivasa Raju and Nageshkumar 2004). Even after the optimization there is a considerable percentage of spills and this is due to the limitation of the capacity of the reservoirs. In the case of Periyar reservoir the spill is more and is due to the proportionately high flow in that case, compared to Kovilar reservoir. The cumulative spill from the individual reservoirs is expressed in terms of the percentage of the reservoir capacity in figure 5.3. Even though the spillage duration is very short, the quantity of water spilled is a considerable value of 45.82% in the case of Periyar reservoir and this is due to the fact that the inflow is concentrated in a short span of time in a year. In the given type of climatic conditions this is unavoidable in spite of the optimization. The cumulative spill for the Kovilar is 3.76%.

![Cumulative spill after optimization as percentage of reservoir capacity](image.png)

**Figure 5.3** Cumulative spill after optimization as percentage of reservoir capacity [Case 1(a)]
5.4.2 Two lead with forecast inflow [Case 1(b)]

For the efficient management of an irrigation system knowing the demand and supply of water is essential. As the type of crop and the area of cultivation are known the demand is also fairly known. In this regard to take decisions regarding the release of water, accurate forecast of inflow into the reservoir is inevitable. The forecasted inflow using ANN as detailed in chapter 4 is used as input for optimization with 2 time steps. The forecasted inflow values with storage and demand are given as inputs to the GA model. The optimized release values obtained using the forecasted inflows and the actual inflows are compared in figure 5.4. The optimized release pattern using the forecasted values of inflow closely follows the release pattern obtained using the actual inflows. The peak demand during the crop season occurs in the 8th fortnight and was 5.488Mm$^3$ of which 4.23Mm$^3$ was met by the release from reservoirs under optimized operation using the actual inflows resulting in a deficit of 1.65 Mm$^3$.

However the release was substantially reduced to 3.13Mm$^3$ in the case of forecasted inflow based optimization and this may be due to the underestimated inflows by ANN due to noisy data. However, this demonstrates the feasibility of application of GA based reservoir operation optimization combined with ANN based flow forecasting in real time applications. Jay.R Lund et al (1996) have reported that optimal releases were found to be better determined by inflows at various locations rather than reservoir storage. They have concluded that deterministic optimization using historic inflows is not outdated. The best release rules were found to be the functions of upstream and down stream inflows only.

Jan-Tai Kuo et al (1990) have also emphasized the importance of inflow forecasting in determining optimal reservoir release policies. They
have analysed the effect of 10 days ahead streamflow forecast in deriving 10 days optimal reservoir release policies. They have concluded that including the exogenous input like precipitation data in forecast will improve the performance.

![Comparison of optimized release values using forecasted and actual inflows (for 2 time leads).](image)

**Figure 5.4** Comparison of optimized release values using forecasted and actual inflows (for 2 time leads).

In figure 5.5 the cumulative releases and combined storages achieved for both actual and forecasted inflows are given.
Figure 5.5 Cumulative releases and storages.

The percentage deviations of deficit and target storage for this case are shown in figure 5.6. As in the case of optimization with actual inflow data, in this case also the deficit is brought to zero during the peak demand, however during the other season the deficit is slightly high. While comparing results with the case 2 graph given in figure 5.2, the maximum demand deficit has increased from 90.39% to 99.82%, this is clearly due to the underestimated inflows during the forecasting. The target storage is not met especially during the non peak demand and this is primarily due to the priority given to the primary objective of reducing the deficit in the optimization process.
Figure 5.6 Demand and storage deficits in percentage

Figure 5.7 gives the cumulative spill after optimization expressed as a percentage of reservoir capacity. Compared to the previous case-1(a) as shown figure 5.3, in this case the cumulative spill for Periyar reservoir has increased from 3.76% to 34.30%. In the case of Kovilar reservoir there is no spill at all, whereas in case 1 the cumulative spill was 45.81% of the reservoir capacity. The above facts are indicators of the better management of water resources; however the reduction in the predicted inflows compared to the actual inflows also could be a contributory factor for the change in spill.
Figure 5.7 Cumulative spills after optimization as percentage of reservoir capacity [Case 1(b)]

5.4.3 Two lead with best forecast inflow [Case 1(c)]

Dagli and Miles (1980) attempted to find a method of determining operating policies for a set of 4 dams based on the inflow forecast. They used 2 methods known as ‘Adaptive planning’ (AP) and Complete Knowledge Run (CKR). They have concluded that the difference in results obtained from both the methods was mainly attributed to inflow forecast errors. They have also emphasized the need for ‘best’ forecasting model for any given problem. Based on the above observation best inflow forecast is attempted by preprocessing the original data.

As the actual inflow data is highly noisy, it is necessary to preprocess the data to yield meaningful results during the neural network training. The inflow data was preprocessed with different techniques and the
singular spectrum analysis (SSA) is found to yield the best results and hence
the forecasted inflows using SSA is taken as the input in addition to initial
storage and demand for optimization. The above data in two time steps (n=2)
is used for the fitness function optimization using GA. As the filtered data
yields more accurate predictions, the optimization also becomes more
effective and is reflected in the reduced deficits when compared with results
of unfiltered data. Figure 5.8 shows the effect of data preprocessing on
optimization in terms of reduced deficits. The maximum percentage reduction
in deficit is 100% and the average reduction is 34.6%.

The percentage deviations in demand deficit and target storage
remain with out much change and are shown in figure 5.9. The maximum
value of demand deficit in this case is 84.02% as compared to the case 1(b)
where the value is 99.82%. The maximum deviation in target storage is again
taking place during the peak flow period as anticipated. The maximum value
of storage deficit in this case again is 100%. The impact of improvement in
the inflow forecast quality owing to the preprocessing of data is not fully
translated into benefits in this case and this may be due to the cumulative
nature of errors in the sequential processing of inflow forecasting and release
optimization. Another reason may be short time horizon and the effects are
likely to be more pronounced in the case of higher values of time horizons.
Figure 5.8 Effect of preprocessing of data on optimization in terms of reduced deficits.

Figure 5.9 Demand and storage deficits in percentage.
In this case spill from Periyar reservoir is more and is again due to the proportionately high flow in that case compared with Kovilar reservoir. The cumulative spill from the individual reservoirs is expressed in terms of the percentage of the reservoir capacity in figure 5.10. Even though the spillage duration is very short, the quantity of water spilled is a very high figure of 280.05% in the case of Periyar reservoir and for the Kovilar reservoir the corresponding figure is 38.80%. This again is an indicator of inefficient management of water primarily due to the limited storage capacity of reservoirs and since a major part of the total flow occurs in a very short span of time. As mentioned earlier, the reservoirs are small in size and constructed only to impound only 30% of flood flows. Eventually if high inflow enters into reservoir during heavy rainy seasons, the huge spill becomes unavoidable.

![Cumulative spills after optimization as percentage of reservoir capacity](image)

**Figure 5.10** Cumulative spills after optimization as percentage of reservoir capacity [Case 1(c)]
5.4.4 Four lead with actual inflow [Case 2(a)]

As the forecast horizon increases the accuracy of prediction decreases. To study the impact of the above effect on the subsequent optimization process and to assess the acceptability of the results, in this case, optimization is done with four time steps (n=4) with actual inflow, initial storage and demand data as inputs. Figure 5.11 shows the performance of the optimized release pattern in terms of deficit with 2 lead and 4 lead actual inflows. In the case of optimization for a period of 4 time steps with actual data, the deficits are found to reduce marginally. This may be attributed to the fact that long term planning results in better utilization of resources and lesser wastage. However, it is not feasible to forecast inflows accurately for long time horizons and this lack of accuracy will offset the advantage of long term planning and will lead to inefficient management of resources. The above hypothesis is further illustrated in the subsequent cases. Campolo et al (1999) have also concluded that forecast accuracy decreases with a longer time horizon.

![Figure 5.11 Optimized deficits with 2 lead and 4 lead actual inflows.](image-url)
The impact of lead time on the storage performance of the system under optimized release conditions with actual inflow data is shown in figure 5.12. Here again the reservoir volume is found to be better utilized in the case of longer term planning as we are using the actual inflow data. This will not be the case with real time situations as there is no way to know the future inflows with zero error.

![Figure 5.12 Optimized storage values using actual inflows (2 and 4 - lead)](image)

The demand and storage deficits are expressed in terms of percentage in figure 5.13. Both the deficits are due to the insufficient inflows during the peak demand periods.
Figure 5.13 Demand and storage deficits in percentage

Figure 5.14 gives the cumulative spill after optimization expressed as a percentage of reservoir capacity and compared to the previous case as shown figure 5.3, in this the cumulative spill for Periyar reservoir has reduced from 45.82% to virtually no spill situation (0.00095%). In the case of Kovilar reservoir again there is only a minimal spill in this case (0.0016%), whereas in case 1(a) the cumulative spill was 3.76% of the reservoir capacity. The above facts are indicators of the better management of water resources; however the reduction in the predicted inflows from the actual inflows also could be a contributory factor for the reduction in spill.
5.4.5 Four lead with forecast inflow [Case 2(b)]

In this case inflow data forecasted with 4 time steps is used as one of the inputs of the optimization using GA. As the forecast time horizon is increased the level of accuracy is affected and is reflected in the system in terms of increased deficit. This is illustrated in figure 5.15. The overall demand deficits from the model for the season with 2 and 4 lead forecasted inflows are 29.85Mm³ and 30.92Mm³ respectively. There is a marginal increase in the demand deficit with 4 lead model and this is due to the impact of reduced accuracy in inflow predictions with longer time horizons. In Figure 5.16, impact of time horizon in terms of combined storage volume is demonstrated. The peak storage values for 2 and 4 leads are 2.88Mm³ and 3.21Mm³ respectively. Even though as the planning period increases there is an improvement in the utilization of storage volume of the reservoirs, this is
not translated into reduction in deficit. This again may be due to the increasing error in terms of underestimated inflows.

![Figure 5.15 Optimized deficits with 2 lead and 4 lead actual inflows](image)

![Figure 5.16 Optimized storage values using forecasted inflows (2-lead and 4-lead)](image)
The demand and storage deficit are expressed in terms of percentage in figure 5.17. The maximum value of demand and storage deficit in this case is 100%. The maximum deficit in storage is again taking place during the peak flow period as anticipated due to the high release.

![Demand and storage deficits in percentage](image)

**Figure 5.17 Demand and storage deficits in percentage**

The cumulative spill from the individual reservoirs is expressed in terms of the percentage of the reservoir capacity in figure 5.18. In this case there is no spill from Kovilar reservoir and there is a cumulative spill amounting to 58.5% of the storage capacity of the Periyar reservoir. Even though the spillage duration is very short, the 58.5% spillage in the case of Periyar reservoir is due to the gross underestimation of the inflows as a result of the long time horizon.
5.4.6 Four lead with best forecast inflow [Case 2(c)]

From the analysis of forecasted inflows from section 4.4.2 it is evident that, there is no significant improvement with preprocessed data using ANN beyond 2 leads and hence GP is adapted to further improve the accuracy of predictions for 3rd and 4th leads. In this case the 4 lead predicted inflows using ANN and GP from section 4.4.3 are used in the optimization model. Figure 5.19 shows the demand deficit for the optimization model for 4 lead together with the results of case 1(c). In this case also there is no advantage with increased time lead in optimization due to the errors in the flow prediction. The cumulative deficits for the season with 2 lead (ANN) and 4 lead (ANN and GP) forecasted inflows are 21.26 Mm$^3$ and 30.91 Mm$^3$ respectively. The variation in the storage for both 2 lead and 4 lead cases are shown in figure 5.20. From the above observation it may be concluded that

Figure 5.18 Cumulative spills after optimization as percentage of reservoir capacity [Case 2(b)]
short time lead (2 lead) is better for the optimization mainly due to the improved accuracy of short term inflow predictions using ANN.

Figure 5.19 Optimized deficits with 2 lead and 4 lead actual inflows

Figure 5.20 Optimized storage values using actual inflows (2-lead and 4-lead)
In this case again the percentage deficits in demand and storage remains without significant deviations from expectations and is shown in figure 5.21. The maximum values of demand as well as storage deficits are 100%. The maximum deficit in target storage is again taking place during the peak flow period as anticipated.

![Demand and storage deficits in percentage](image)

**Figure 5.21 Demand and storage deficits in percentage**

The cumulative spill from the individual reservoirs is expressed in terms of the percentage of the reservoir capacity in figure 5.22. In this case again there is no spill from Kovilar reservoir and the cumulative spill from the Periyar reservoir is 58% of the storage capacity. Here again the erroneous forecasted inflow data is the reason behind the error in optimization. This warrants the need for accurate inflow forecast for longer time horizons.
5.5  LINEAR PROGRAMMING FOR OPTIMIZATION

The primary challenge in reservoir operation model lies in the extent to which risk and uncertainty issues in the hydrologic data are accounted in the modeling formulation. The most important variables in this context are reservoir inflow, rain fall in the irrigated command area, and crop water demands. To compare the results of optimization obtained for various models using GA, a Linear Programming (LP) model is also used and the optimization is carried out using a linear programming tool.

In Linear Programming problems there is a single objective function to be maximized or minimized (subject to constraints). In some problems there may be more than one competing objective (or goal) and we need to trade-off objectives against each other. One way of handling problems
with multiple objectives is to choose one of the goals as the supreme goal and to treat the others as constraints to ensure that some minimal ‘satisfying’ level of the other goals is achieved.

However, Linear Programming provides a more satisfactory treatment where in many cases problems can still be solved using standard Linear Programming algorithms. In our problem there are competing multi objectives namely demand deficit and target storage. By keeping the demand deficit as well as storage deficit to be minimum, the reservoir operation optimization is performed using Linear programming and the results are compared with that of GA. The Linear programming implementation is done with the tool LINDO 5.02. The modified mathematical formulation of objective function in accordance with the requirements of LINDO is as follows.

\[
\text{Minimize } Z = \sum_{i=1}^{n} \left( (PR_i + KR_i) - D_i \right) + \left( (PS_n + KS_n) - T_s \right) \tag{5.9}
\]

In figure 5.23 the deficit for optimization models using GA and Linear programming using forecasted inflows with preprocessed data for 2 leads in ANN is shown. In this case the deficit for GA model is evidently smaller compared to that of Linear model and it is concluded that the GA model with forecasted data using ANN with preprocessing is good enough for short time horizons.
Figure 5.23 Deficits with GA and LP models

Similar kind of comparison of GA results with LP is reported by Wardlaw and Sharif (1999). They have concluded that GA is robust and flexible in application to non-linear problems. Srinivasa Raju and Nageshkumar (2004) have compared the results obtained by GA with LP for evolving optimal cropping pattern and reservoir operation policies for a reservoir. They have reported that the solutions obtained by GA and LP were reasonably close. They have concluded that GA is found to be an effective optimization tool for irrigation planning and can be applied for more complex systems involving non-linear optimization.

The combined reservoir storage attained using the GA and LP models are shown in figure 5.24. In the case of LP model there are two peaks in the storage curve whereas there is only one peak in the case of GA model. This pattern is a repetition of the twin peaks in the case of LP model deficit as shown in figure 5.23.
The deficit values with GA and LP models for 4 leads are shown in figure 5.25. As in the case of 2 leads, here again the GA proves to be superior with lesser deficit. The total deficit with GA model is found to be 21.38Mm$^3$ and the corresponding value for LP model is 23.80 Mm$^3$.
5.6 COMPARISON OF VARIOUS MODELS

The effect of actual and forecasted inflow data on the efficiency of optimization with GA model in terms of demand deficits for 2 lead and 4 lead times is shown in figures 5.26(a) and 5.26(b). The lowest deficit is obtained when 4 lead actual inflows are used and the highest deficit is in the case of 4 lead forecast inflow. The poor performance in the case of 4 lead forecasted data underlines the need for preprocessing of data and the probability of increased errors in the case of long time horizon forecasting. The cumulative deficits for various cases are presented in table 5.2.

![Graph showing the effect of flow forecasting on GA model deficit (2-lead Actual, Forecast and Best forecast)](image)

Figure 5.26(a) Effect of flow forecasting on GA model deficit (2-lead Actual, Forecast and Best forecast)
Figure 5.26(b) Effect of flow forecasting on GA model deficit (4-lead Actual, Forecast and Best forecast)

Table 5.2 Cumulative deficits for various models

<table>
<thead>
<tr>
<th>Sl. No</th>
<th>Model</th>
<th>Cumulative deficit (Mm$^3$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Two lead actual flow model</td>
<td>20.84</td>
</tr>
<tr>
<td>2</td>
<td>Two lead best forecast model</td>
<td>21.26</td>
</tr>
<tr>
<td>3</td>
<td>Two lead forecast model</td>
<td>29.85</td>
</tr>
<tr>
<td>4</td>
<td>Four lead actual flow model</td>
<td>20.17</td>
</tr>
<tr>
<td>5</td>
<td>Four lead best forecast model</td>
<td>30.91</td>
</tr>
<tr>
<td>6</td>
<td>Four lead forecast model</td>
<td>30.92</td>
</tr>
</tbody>
</table>

Similarly, the effect of inflow data on the efficiency of optimization with GA model in terms of the combined reservoir storage is shown in figure 5.27(a) and 5.27(b). The lowest storage is obtained when 2 lead forecast inflows are used and the highest storage is in the case of 4 lead best forecast
inflow. As far as demand deficit is concerned, the lowest demand deficit is not achieved in this case. This indicates that a higher storage need not be an indicator of higher efficiency of an irrigation system.

**Figure 5.27(a) Effect of flow forecasting on GA model storage (2-lead Actual, Forecast and best forecast)**
Figure 5.27(b) Effect of flow forecasting on GA model storage (4-lead Actual, Forecast and Best forecast)

5.7 COMPARISON OF ACTUAL AND OPTIMIZED RELEASES AND OPTIMIZED STORAGES

The effect of optimization in terms of releases in various cases of inflow prediction is presented in figures 5.28(a) to 5.28(f). In all the cases the trend of the optimized release pattern closely resembles the actual demand pattern. This is a clear indication that as a result of optimization the releases are modified to better meet the demand. Among the optimized releases the 4 lead actual flow model yields the best result followed by the 2 lead actual flow model and the 2 lead best forecast models. The cumulative release values are shown in table 5.3.
Figure 5.28(a) Comparison of optimized release and actual release (2-lead Actual flow model)

Figure 5.28(b) Comparison of optimized release and actual release (2-lead Best forecast model)
Figure 5.28(c) Comparison of optimized release and actual release (2-lead Forecast model)

Figure 5.28(d) Comparison of optimized release and actual release (4-lead actual flow model)
Figure 5.28(e) Comparison of optimized release and actual release (4-lead Best forecast model)

Figure 5.28(f) Comparison of optimized release and actual release (4-lead Forecast model)
Table 5.3 Cumulative release values for various models

<table>
<thead>
<tr>
<th>Sl. No</th>
<th>Model</th>
<th>Cumulative release (Mm³)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Two lead actual flow model</td>
<td>20.75</td>
</tr>
<tr>
<td>2</td>
<td>Two lead best forecast model</td>
<td>20.33</td>
</tr>
<tr>
<td>3</td>
<td>Two lead forecast model</td>
<td>11.73</td>
</tr>
<tr>
<td>4</td>
<td>Four lead actual flow model</td>
<td>21.42</td>
</tr>
<tr>
<td>5</td>
<td>Four lead best forecast model</td>
<td>20.22</td>
</tr>
<tr>
<td>6</td>
<td>Four lead forecast model</td>
<td>10.67</td>
</tr>
</tbody>
</table>

The effect of optimization in terms of storage for the various cases of inflow prediction is presented in figures 5.29(a) to 5.29(f). As a result of the optimization, in all the cases the storage has reduced substantially and this is indicative of the fact that as a result of the optimization the water is better utilized to meet the demands. The above trend is also evident from the release patterns discussed earlier.
Figure 5.29(a) Comparison of optimized storage and actual storage
(2-lead Actual flow model)

Figure 5.29(b) Comparison of optimized storage and actual storage
(2-lead Best Forecast Model)
Figure 5.29(c) Comparison of optimized storage and actual storage 
(2-lead forecast model)

Figure 5.29(d) Comparison of optimized storage and actual storage 
(4-lead Actual Flow Model)
Figure 5.29(e) Comparison of optimized storage and actual storage (4-lead Best Forecast Model)

Figure 5.29(f) Comparison of optimized storage and actual storage (4-lead Forecast Model)
5.8 CLOSURE

In this chapter, the reservoir operations are optimized using GA and compared with Linear programming with actual and predicted inflows. As the effectiveness of optimization is a function of the quality of the forecasted inflow, the demand deficit and target storage are found to be affected by the type of inflow inputs given. The inflows used are the ones predicted for short and long time horizon using ANN and GP as in chapter 4. It has been observed that in the case of short lead, even though the forecasting is more accurate, the optimization is less effective due to the short planning period. However in the case of long lead the advantage of long term planning in the optimization is offset by the decreasing accuracy in the forecasted inflows which are used as inputs.