Multiobjective Optimization Applied to the Distribution of Petroleum Products in Pipelines Networks

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Abstract

Constraints satisfaction and multiobjective optimization are very common in real-world optimization scenarios and cannot be handled independently of the underlying optimizer. Heuristics methods are especially well suited to solve these complex problems. Genetic algorithms can be very robust and easy to be implemented if compared to a numerical method. In this paper, a problem of petroleum products distribution through pipelines networks is proposed. It considers a simplified model of a real network. The methodology uses a GA with an elitism strategy to find a set of feasible solutions. The Global Criterion Method and an approaching of Weighing Objectives Method were used to calculate the fitness of each individual in this set.

Keywords: Optimization, Multiobjective, Genetic Algorithm, Global Criterion, Petroleum Distribution, Pipelines Network.

1. Introduction

Genetic algorithms (GAs) were inspired by the principle of natural selection of individuals, where the most “capable” tends to remain in the population and reproduce, passing its genetic code onto the next generation. In
almost cases, this method can achieve good solution when compared with
conventional methods of optimization.

2. Model of the network

A problem of distribution of petroleum products through pipelines
networks is proposed. It considers a simplified model of a real network. The
network is composed by two sources (Node 1 and Node 2) that represent
refineries, two intermediate connection (Node 3 and Node 4) that ac
as sinks or sources with storage capacity and three terminals (Node 5, Node 6 and Node 7).
The arrows represent the polyducts that connect the nodes each others and its
respective direction. A bidirectional pipe is introduced to connect the two
intermediates nodes. Figure 1 shows the model of this network.

![Figure 1 - Distribution network](image)

It is assumed that the products are delivered as discrete batch, each
terminal or intermediate node have as many tanks as products it can receive, to
store the different products. All the connections have the same characteristics as
diameter, volume, flow speed and etc. A batch is a product volume delivered
by a source or intermediate node. $D_1$, $D_2$, ..., $D_9$ are normalized distance in
terms of unit time needed to a batch to be delivered from one node to another
one. It means the time that a batch takes to be transported from one node to
another one.

3. Solution Codification

The solution of the problem is given by the type of the batch sent by
every node at every instant. To code the solution, a matrix is used to represent
the population, where each row represents an individual. The individual is
divided by time instants and each instant divided by the number of connections.
Each element stored in the matrix represent the type of the batch sent through
the connections. For example, the first $n$ elements of an individual will represent the batch type sent through the $n$ connections in the first time instant. The following $n$ elements the batch type sent during the second time instant, and so on.

The figure 2 shows the individual codification for 10 instants. The values are in the range $[0; \text{number of products}]$, where 0 represents an empty connection.

<table>
<thead>
<tr>
<th>Time</th>
<th>Instant 1</th>
<th>...</th>
<th>Instant 10</th>
<th>...</th>
</tr>
</thead>
<tbody>
<tr>
<td>Connection</td>
<td>1</td>
<td>...</td>
<td>10</td>
<td>...</td>
</tr>
<tr>
<td>Solution</td>
<td>1 0 1 2 3 3 0 2 3</td>
<td>...</td>
<td>2 4 3 0 2 2 3 0 3</td>
<td></td>
</tr>
</tbody>
</table>

Figure 2 - Solution codification

A mask is used to handle nodes that produce different types of products. In the model, node 1 produces type 1 and 2, and node 2 produces type 3 and 4. Therefore connections $D_1$ and $D_2$ can handle only product type 1 and 2, and so on. Table 1 shows the entry values of mask.

<table>
<thead>
<tr>
<th>Connection</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mask</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>4</td>
</tr>
</tbody>
</table>

Table 1 – Mask product codification

Using the mask, the range for connection 1 to 4 is in $[0; 2]$. Then, just values inside this range can be found in the solution codification for connection 1 to 4. A matrix containing ‘i’ connections and ‘j’ products is used to decode the mask as shown in table 2. The stored value of the decoder matrix is the batch type. Therefore, the pair $(i,j)$ gives the batch type, where the ‘$i$’ is the connection and ‘$j$’ the element stored in the code solution.

<table>
<thead>
<tr>
<th>Coding values</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Connection $D_1$</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Connection $D_2$</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>Connection $D_9$</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
</tbody>
</table>

Table 2 – Decoder matrix

4. Genetic Operators

Genetic operations are the tools allowing the exploration of search space, and they are responsible to find new solutions and to converge the model to a good solution. The main genetic operations are the crossover, mutation and selection and in this paper, they are implemented as described in [1]. Moreover, we use an elitism strategy where a set of good solution is kept generation by generation. This strategy avoids to loose good solution during the generation [2] and in the end of evolution, the decision-maker can choose a solution from a set
of potential solutions for the multiobjective optimization problem in addition to the best individual representing the final unique solution. Figure 3 shows the selection method used in this work.

![Selection method](image)

**Figure 3 – Selection method**

# 5. Multiobjective Optimization

To calculate the fitness, it was used the Global Criterion Method and an approaching of Weighing Objectives Method [3] as following:

$$\text{fitness} = \frac{\sum_{i=0}^{N_0} w_i \cdot f_i}{\sum_{i=0}^{N_0} w_i}, \quad \text{to } w_i \geq 0$$  \hspace{1cm} \text{Eq.(1)}

$w_i$ is the weigh for each objective ‘$i$’.

The best fitness has the value 0 and the worst fitness has the value 1.

The model is subject as the following constraints:

1. There must be no collisions of batches in the bidirectional connection.
   $$NC = 0$$  \hspace{1cm} \text{Eq.(2)}

2. The number of batches in the tanks can not violate the lower and upper limit for each node ‘$i$’ and product ‘$j$’.
   $$LCm_{ij} \leq C_{ij} \leq LCM_{ij}$$  \hspace{1cm} \text{Eq.(3)}

   The constraints are fulfilled by reparation function as described in [4].

   The objectives number 1 and 2 are constraints that are treated as objectives. The objectives are the follow equations:

1. Satisfy the minimal production:

   $$\text{mim} = \sum_{j=0}^{N_f} \sum_{i=0}^{N_1} \left( \begin{array}{l}
   1 \quad E_{ij} \leq P_{ij} \\
   0 \quad E_{ij} > P_{ij}
   \end{array} \right)$$  \hspace{1cm} \text{Eq.(4)}

   $P_{ij}$ is the minimal number of batches to be sent from the source and $E_{ij}$ is the amount of batch sent, for each source ‘$i$’ and product ‘$j$’.
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2. Receive the amount of batches demanded \((D_{ij})\) by terminals:

\[
mim \sum_{i \in I} \sum_{j \in J} \left( \frac{1 - R_{ij}}{D_{ij}} \right) N_d
\]

\(Eq.(5)\)

\(R_{ij}\) is the number of batches of product ‘\(i\)’ in the terminal ‘\(j\)’ received.

3. Minimize the time of delivery for batches. The portion \(\left( D_{ij} - R_{ij} \right) \) is a penalty in case of the demand won’t be fulfilled.

\[
mim \sum_{i \in I} \sum_{j \in J} \left( \frac{T_{arrival_{ij}} - T_{min} + (D_{ij} - R_{ij})}{N_d} \right)
\]

\(Eq.(6)\)

\(T_{arrival_{ij}}\) is the arrival time of a batch of the product ‘\(i\)’ in the terminal ‘\(j\)’, \(T_{max}\) is the horizontal time and \(T_{min}\) is the smallest time for a batch to be received in a terminal.

4. Minimize the batches changes or fragmentations:

\[
mim \sum_{i \in I} \sum_{j \in J} \left( \frac{\left( \frac{\text{Frag}_i}{N_{\text{conex}}} \right)}{\left( \text{Mask}[i] \right)} \right)
\]

\(Eq.(7)\)

\(\text{Frag}_i\) is the number batches changes in the connection ‘\(i\)’.

6. Results

To run the model it is necessary to configure the upper and lower tank limit, the time distance of each connection and horizontal time. These configurations are a project decision. Figure 4 shows the evolution of the global objective function and objective 1 during the generations.

Figure 4 – (a) Global objective fitness, (b) Objective 1
Figure 5 shows the evolution of objective 2 and objective 3 during the generations.

Figure 5 – (a) Objective 2, (b) Objective 3

Table 3 shows the values of all objectives achieved after the simulation.

<table>
<thead>
<tr>
<th>Objective</th>
<th>Global</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fitness value</td>
<td>0.049</td>
<td>0</td>
<td>0</td>
<td>0.34</td>
<td>0.03</td>
</tr>
</tbody>
</table>

Table 3 – Final values of the objectives

The global objective is very close to zero, it means a result close to the optimum. Objective 1 and 3 were accomplished, but objective 3 and 4 were partially achieved. It can be noted that the model converges quickly and good solution are not loosed during the generations because the selection method implemented.

7. Conclusions

A distribution problem of petroleum through pipelines network was presented and optimization methods were described. Genetic algorithm can be a powerful tool to solve complex problems as show in this work and good solution can be achieved.

References