## **Supplementary Materials**

**A.5 Performance measures**

To compare the quality and diversity of the solutions generated by each method, several metrics are applied.

*Quality Metric (QM)*: This metric compares the number of non-dominated solutions obtained by each algorithm with the total number of non-dominated solutions found. A higher QM indicates better performance.

*Mean Ideal Distance (MID)*: MID calculates the average distance from the ideal point of (*f1best*, *f2best)* (also known as the utopia values). Lower MID values are preferred. For this measure, the average of Euclidean distance of non-dominated solutions and the ideal point are calculated (Coello, 2007; Hasani Goodarzi et al., 2020). The mathematical formulation of the MID for the proposed model is presented in Eq (A-49). It considers the cost and risk objectives of each Pareto solution along with the best and worst values of these objectives. In Figure 4 of the main document, distance to the ideal point for each pareto solution is also reported.

|  |  |
| --- | --- |
|  | (A-49) |

Where and are the values of cost and risk objective functions for *jth* Pareto solution, respectively, and are the minimum values of cost and risk objectives, respectively, and and are the maximum values of these objective functions. N is the number of non-dominant solutions generated by each algorithm.

*Diversification Metric (DM)*: DM measures the spread of the solution set (Zitzler et al., 2000). It calculates the range of Pareto-front solutions found by each method in terms of cost () and risk objectives (). DM is obtained from Eq (A-50).

|  |  |
| --- | --- |
|  | (A-50) |

*Spacing Metric (SM)*: SM evaluates the average distance between each solution and its nearest neighbor within the solution set (Deb et al., 2000). It assesses the variance and diversity of neighboring solutions in the Pareto front. The SM is calculated using Eq (A-51).

|  |  |
| --- | --- |
|  | (A-51) |

*n* represents the number of solutions, where is the Euclidean distance between consecutive solutions in the obtained non-dominated solution set by each method, and represents the mean value of these distances. A smaller value of this metric indicates a more uniform distribution of the obtained front.

**References**

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