On the Use of Evolutionary Optimization for the Dynamic Chance Constrained Open-Pit Mine Scheduling Problem

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***Abstract*—Open-pit mine scheduling is a complex real-world optimization problem that involves uncertain economic values and dynamically changing resource capacities. Evolutionary algorithms are particularly effective, as they can easily adapt to such environments. However, uncertainty and dynamic changes are often studied in isolation in real-world problems. In this paper, we study a dynamic chance-constrained open-pit mine scheduling problem where block economic values are stochastic and mining and processing capacities vary over time. We adopt a bi-objective evolutionary formulation that simultaneously maximizes expected discounted profit and minimizes its standard deviation. To address dynamic changes, we propose a diversity-based change response mechanism that repairs a subset of infeasible solutions and introduces additional feasible solutions whenever a change is detected. We evaluate the effectiveness of this mechanism across four multi-objective evolutionary algorithms and compare it with a baseline re-evaluation–based change-response strategy. Experimental results demonstrate that the proposed approach consistently outperforms the baseline methods across different uncertainty levels and change frequencies.**

***Index Terms*—Open-pit mine scheduling, Dynamic optimization, Multi-objective evolutionary algorithms, Chance-constraints**

I. Introduction

The open-pit mine scheduling problem (OPMSP) is a large-scale combinatorial optimization problem that determines the optimal sequence of block extraction from a mining deposit to maximize the net present value (NPV), while satisfying geological and operational constraints. Over the years, it has been widely studied using many optimization approaches, including exact methods [1], heuristics [2], and metaheuristics [3, 4].

However, real-world mining operations involve significant uncertainty and dynamic changes, including stochastic ore grades, commodity price fluctuations, equipment downtime, weather conditions, and time-varying mining and processing capacities. Ignoring these factors can lead to infeasible or suboptimal production schedules, reduced economic returns, and compromised operational safety [5].

Several approaches have been proposed to address OPMSP under uncertainty, including exact methods [5], metaheuristics [6, 7], and hybrid methods [8]. Incorporating both aspects is essential to avoid operational bottlenecks such as mill overloads or deviations between planned and actual ore grades, enabling efficient and feasible mine plans.

Evolutionary algorithms (EAs) are particularly effective for stochastic and dynamic optimization problems due to their flexibility and robustness [9, 10, 11]. To handle uncertainty explicitly, chance-constraints [12] can be used in optimization problems, ensuring that stochastic constraints are satisfied with a predefined confidence level, α. Among them, multi-objective evolutionary algorithms (MOEAs) are particularly effective, as they enable the simultaneous optimization of multiple stochastic components, such as the expected value and variance [10, 11]. In this paper, we investigate the dynamic chance-constrained open-pit mine scheduling problem with stochastic profits and dynamically changing resource capacities.

A. Related Work

The OPMSP has been widely studied due to its economic importance and computational complexity using exact methods [1], heuristics [2], metaheuristics such as differential evolution [3], EAs [4], and hybrid approaches [8]. While early work assumes deterministic geological models, more recent studies adopt ensemble-based representations to capture spatial grade uncertainty [7, 13]. For instance, Stimson et al. [7] proposed a single-objective evolutionary approach for the chance-constrained OPMSP using discounted profits across realizations, but requiring a fixed confidence level α.

Evolutionary algorithms have shown strong performance on stochastic and dynamic optimization problems, including knapsack and submodular optimization [14, 15, 16, 17], where MOEAs often outperform single-objective methods. They have also been successfully applied to dynamic hydro-thermal scheduling [18].

Only limited work considers stochastic and dynamic optimization simultaneously. In [9], a dynamic chance-constrained knapsack problem was studied using MOEAs, but requiring separate runs for different α. This limitation was addressed by three-objective formulations that eliminate the need to predefine α [10, 11]. Recent work on stochastic and dynamic multiple knapsack problems [19] further demonstrates the effectiveness of MOEAs. These studies motivate the application of MOEAs to the dynamic chance-constrained OPMSP considered in this paper.

B. Our Contribution

To the best of our knowledge, this is the first work to investigate the chance-constrained OPMSP in dynamic environments using MOEAs. We assume that block economic values follow normal distributions, while mining and processing capacities vary over time. The problem is formulated as a bi-objective optimization model that maximizes expected NPV and minimizes its standard deviation, capturing the trade-off between profit and risk. By explicitly modeling risk as a separate objective, this approach eliminates the need to predefine a confidence level, enabling MOEAs to generate solutions across a range of α values in a single run.

To handle dynamic changes, we introduce a diversity-based change-response mechanism that repairs a subset of infeasible solutions and introduces additional feasible solutions whenever a change is detected. This mechanism is integrated into four MOEAs, MOEA/D, NSGA-II, SMS-EMOA, and SPEA2, and is compared against re-evaluation–based baselines. Experimental results on six mining instances show that the proposed approach consistently outperforms the baselines under varying uncertainty levels and dynamic change frequencies.

The remainder of the paper is organized as follows. Section II presents the proposed method. Section III and IV present the experimental setting and results. Finally, Section V concludes the paper.

II. Open Pit Mine Scheduling Problem with Stochastic Profits and Dynamic Resource Constraints

This section defines the dynamic chance-constrained OPMSP, its bi-objective problem formulation, and the change-response mechanism.

A. Problem Definition

We consider a dynamic chance-constrained open-pit mine scheduling problem (DCC-OPMSP), in which block economic values are stochastic and resource capacities vary over time.

Let $\mathcal{B}$ denote the set of mineable blocks, and $\mathcal{T} = \{1, \ldots, T\}$ denote the planning periods. A schedule is represented by binary decision variables $x = \{x_b^t \mid b \in \mathcal{B}, t \in \mathcal{T}\}$, where $x_b^t = 1$ if block b is mined in period t, and $x_b^t = 0$ otherwise. Let $\mathcal{P}$ denote the set of precedence constraints, where $(a, b) \in \mathcal{P}$ means that block a must be mined before block b. Let $\mathcal{R}$ be the set of resources. For each resource $r \in \mathcal{R}$, block b consumes r_b units, and R_r^t denotes the available capacity of resource r in period t.

Each block $b \in \mathcal{B}$ has a stochastic profit $p_b \sim \mathcal{N}(\mu_b, \sigma_b^2)$, where μ_b and σ_b^2 denote the expected profit and variance of block b, respectively. Block profits are assumed to be spatially correlated, reflecting geological dependencies within the orebody.

For a given schedule x, the total discounted NPV is the random variable $p(x) = \sum_{t \in \mathcal{T}} \frac{1}{(1+d)^t} \sum_{b \in \mathcal{B}} p_b x_b^t$, where d is the discount rate per annum. Since $p(x)$ is a linear combination of jointly normally distributed random variables, it is also normally distributed.

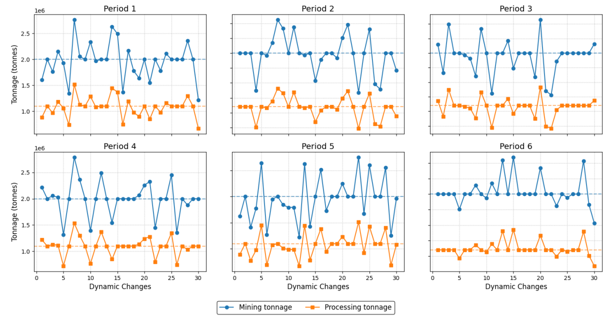

Fig. 1: Dynamic changes in mining and processing capacities over six periods under 30 dynamic changes.

The DCC-OPMSP is formulated as follows:

$$\begin{aligned}
\textbf{Maximize} \quad & P, \\
\textbf{Subject to} \quad & \Pr(p(x) \geq P) \geq \alpha, && (1) \\
& \sum_{\tau=1}^{t} x_a^\tau \geq \sum_{\tau=1}^{t} x_b^\tau, \quad \forall (a, b) \in \mathcal{P},\ t \in \mathcal{T}, && (2) \\
& \sum_{t \in \mathcal{T}} x_b^t \leq 1, \quad \forall b \in \mathcal{B}, && (3) \\
& \sum_{b \in \mathcal{B}} r_b x_b^t \leq R_r^t, \quad \forall r \in \mathcal{R},\ t \in \mathcal{T}, && (4) \\
& x_b^t \in \{0, 1\}, \quad \forall b \in \mathcal{B},\ t \in \mathcal{T}. && (5)
\end{aligned}$$

The objective is to determine a schedule x such that the probability of achieving a discounted NPV of at least P is no less than a confidence level α. Constraint (1) is the chance constraint, Constraints (2)–(4) enforce precedence, single extraction, and resource feasibility, and Constraint (5) defines the binary decision variables. We assume $\alpha \in [1/2, 1)$.

To model dynamic environments, for every τ evaluation, we randomly select a subset of periods and modify their resource capacities. For each selected period, a scaling factor $\gamma \sim \mathcal{U}(1 - \eta, 1 + \eta)$ is sampled, where η controls the magnitude of change, and all resource capacities in that period are multiplied by γ. Figure 1 illustrates an example of these dynamic variations for the Newman1 instance [20], where solid lines show the modified capacities and dashed lines indicate the baseline levels.

B. Chance-Constrained Profit Modeling

We model the chance constraint in (1) using the chance-constrained framework for normally distributed profits in [21], which yields a deterministic risk-adjusted objective:

$$f(x) = \mathbb{E}[p(x)] - K_\alpha \sqrt{\mathrm{Var}[p(x)]}, \tag{6}$$

where K_α is the α-quantile of the standard normal distribution.

The expected discounted profit is $\mathbb{E}[p(x)] = \sum_{t \in \mathcal{T}} \frac{1}{(1+d)^t} \sum_{b \in \mathcal{B}} \mu_b x_b^t$. Let $\mathcal{B}^{\text{ore}} \subseteq \mathcal{B}$ denote the set of ore blocks. The variance of the discounted profit is computed as $\mathrm{Var}[p(x)] = \sum_{t\in\mathcal{T}} \frac{1}{(1+d)^{2t}} \mathrm{Var}_t(x)$, where the period-wise variance is given by

$$\mathrm{Var}_t(x) = \sum_{b\in\mathcal{B}^{\mathrm{ore}}} \sigma_b^2 x_b^t + \max\left(0, \sum_{\substack{b,b'\in\mathcal{B}^{\mathrm{ore}}\\ b\neq b'}} \mathrm{Cov}(b,b')\, x_b^t x_{b'}^t\right)$$

as in [7]. Here, σ_b^2 is the variance of block b, and $\mathrm{Cov}(b,b')$ denotes the covariance between blocks b and b'. These values are estimated from ensemble-based realizations [7], and negative covariance values are truncated to zero to avoid underestimating risk.

C. Bi-Objective Fitness Function

We employ a bi-objective formulation for the DCC-OPMSP:

$$g_{2D}(x) = \big(f_1(x), f_2(x)\big), \tag{7}$$

where $f_1(x)$ maximizes the expected discounted NPV and $f_2(x)$ minimizes its standard deviation.

The objectives are defined as

$$f_1(x) = \begin{cases} \mathbb{E}[p(x)], & \text{if } v(x) = 0,\\ -\,v(x), & \text{otherwise,} \end{cases} \tag{8}$$

$$f_2(x) = \begin{cases} \sqrt{\mathrm{Var}[p(x)]}, & \text{if } v(x) = 0,\\ \mathrm{Var}[p(x)] + M\, v(x), & \text{otherwise,} \end{cases} \tag{9}$$

where $v(x)$ denotes the total resource violation and M is a large penalty constant. The total violation is $v(x) = \sum_{t\in\mathcal{T}} v_t(x)$, where $v_t(x) = \max_{r\in\mathcal{R}} \max\big(0,\, y_r^t - R_r^t\big)$ and $y_r^t = \sum_{b\in\mathcal{B}} r_b x_b^t$ denotes resource usage in period t, with R_r^t its capacity.

This formulation avoids fixing a confidence level α during optimization, as both objectives are independent of α. After optimization, the risk-adjusted objective (Eq. (6)) can be evaluated at different confidence levels to select suitable schedules without re-optimization.

D. Dynamic Change Response Mechanism with Diversity Increase

We modify the resource capacities of a randomly selected subset of periods every τ iterations. When a change occurs, the population is re-evaluated under the updated constraints. However, re-evaluation alone is often insufficient, especially when the population has already converged to locally optimal or infeasible regions [22].

We propose a diversity-increasing change response mechanism for the DCC-OPMSP (Algorithm 1). After a dynamic change, the population is re-evaluated and partitioned into a feasible set F and an infeasible set I. If $|F| < N$, feasibility and diversity are restored in two steps. First, up to 20% of the population is selected from I for repair, bounded by $|I|$, using the hypermutation-based operator (Algorithm 2). In this process, solutions are accepted based on feasibility and lexicographic comparison, prioritizing f_1 over f_2, or by minimizing constraint violation when infeasible. Second, up to 20% of the population is replaced with randomly generated feasible solutions, bounded by the remaining capacity $N-|F|$.

Algorithm 1 Dynamic Change Response Mechanism with Diversity Increase

Require: Population P of size N, mutation operator M
$P \leftarrow \{\mathrm{Evaluate}(s) \mid s \in P\}$
$F \leftarrow \{s \in P \mid v(s) = 0\}, \quad I \leftarrow P \setminus F$
if $|F| < N$ **then**
  $S \leftarrow \mathrm{RandomSelect}(I, \min\{0.2N, |I|\})$
  $F \leftarrow F \cup \{\mathrm{Repair}(s, M) \mid s \in S\}$
  $k \leftarrow \min\{0.2N,\, N - |F|\}$
  $F \leftarrow F \cup \{s_1, \ldots, s_k\}$ where $s_i \sim$ RandomFeasible
  while $|F| < N$ **do**
    $F \leftarrow F \cup \{\arg\min_{u\in I\setminus F} v(u)\}$
  end while
end if
$P \leftarrow F$

Algorithm 2 Repair Mechanism with Hypermutation

Require: Initial solution s, mutation operator M, mutation probability P_m
$s_{\text{best}} \leftarrow s, \quad P_m \leftarrow 2P_m$
while stopping criterion not met **do**
  $y \leftarrow \mathrm{Evaluate}(M(s_{\text{best}}))$
  if $v(y) = 0$ **and** $\big(v(s_{\text{best}}) > 0 \vee (f_1(y), f_2(y)) \prec_{\text{lex}} (f_1(s_{\text{best}}), f_2(s_{\text{best}}))\big)$ **then**
    $s_{\text{best}} \leftarrow y$
  else if $v(y) > 0$ **and** $v(y) < v(s_{\text{best}})$ **then**
    $s_{\text{best}} \leftarrow y$
  end if
end while
return s_{best}

TABLE I: Summary of problem instances from MineLib [20].

Instance	T	Blocks	Predec.	Vars.	Res.	Disc.
Newman1	6	1 060	3 922	6 360	2	0.08
Zuck Small	20	9 400	145 640	188 000	2	0.10
KD	12	14 153	219 778	169 836	1	0.15
Zuck Medium	15	29 277	1 271 207	439 155	2	0.10
P4HD	10	40 947	738 609	409 470	2	0.00
Marvin	20	53 271	650 631	1 065 420	2	0.10

III. Experimental Setting

We use six MineLib benchmark instances [20], including simulated mines (Newman1, Zuck Small, Zuck Medium, Marvin) and real-world deposits (KD: copper; P4HD: gold and copper). Table I summarizes their characteristics.

Block values are modeled as normal random variables [7, 23], with uncertainty represented by 50 ensemble realizations. Grade ensembles are used for Newman1 and Marvin, while profit realizations are generated for other instances. The standard deviation is set to 20% of the mean, and chance constraints use $\alpha \in \{0.6, 0.9, 0.99\}$.

Dynamic changes $\nu \in \{20, 10, 5, 2\}$ are introduced every $\tau = E_{\max}/\nu$ evaluations, where $E_{\max}$ denotes the maximum number of fitness evaluations, with magnitude $\eta = 0.4$.

We use a population size of 20 and a total evalua-

TABLE II: Mean and standard deviation of offline error ($\times 10^6$) under different dynamic change frequencies (ν) and confidence levels (α). The best mean across all algorithms is highlighted in gray, and pairwise comparisons between (–RE) and (–DIV) variants are highlighted in bold.

Inst.	ν	α	MOEA/D-RE(1)		MOEA/D-DIV(2)		NSGA-II-RE(3)		NSGA-II-DIV(4)		SPEA2-RE(5)		SPEA2-DIV(6)		SMS-EMOA-RE(7)		SMS-EMOA-DIV(8)	
			mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
Newman1	2	0.60	7.03	1.12	**0.74**	0.05	12.88	0.00	**1.14**	0.01	12.88	0.01	**1.15**	0.02	12.88	0.00	**1.14**	0.01
		0.90	7.61	1.10	**1.41**	0.05	13.21	0.00	**1.80**	0.01	13.21	0.01	**1.81**	0.02	13.21	0.00	**1.81**	0.01
		0.99	8.19	1.08	**2.08**	0.05	13.55	0.00	**2.47**	0.01	13.55	0.00	**2.48**	0.02	13.55	0.00	**2.48**	0.01
	5	0.60	11.66	1.71	**0.84**	0.04	15.37	0.01	**1.26**	0.01	19.99	0.00	**1.56**	0.30	15.37	0.01	**1.25**	0.01
		0.90	12.16	1.67	**1.50**	0.04	15.64	0.01	**1.92**	0.01	20.12	0.00	**2.22**	0.30	15.64	0.01	**1.91**	0.01
		0.99	12.66	1.63	**2.17**	0.04	15.91	0.01	**2.58**	0.01	20.26	0.00	**2.89**	0.30	15.91	0.01	**2.58**	0.01
	10	0.60	17.32	1.18	**0.93**	0.04	15.41	0.02	**1.36**	0.01	19.66	0.86	**2.18**	0.58	15.41	0.02	**1.35**	0.01
		0.90	17.67	1.16	**1.59**	0.04	15.68	0.02	**2.02**	0.01	19.80	0.84	**2.83**	0.57	15.67	0.02	**2.01**	0.01
		0.99	18.03	1.13	**2.26**	0.04	15.94	0.02	**2.68**	0.01	19.94	0.81	**3.49**	0.57	15.94	0.02	**2.68**	0.01
	20	0.60	20.19	0.61	**0.95**	0.05	16.43	0.40	**1.35**	0.02	17.62	0.46	**2.33**	0.38	16.51	0.28	**1.34**	0.01
		0.90	20.46	0.59	**1.62**	0.05	16.67	0.39	**2.01**	0.02	17.83	0.45	**2.98**	0.38	16.74	0.27	**2.00**	0.01
		0.99	20.72	0.57	**2.29**	0.05	16.91	0.38	**2.67**	0.02	18.03	0.44	**3.64**	0.37	16.98	0.26	**2.66**	0.01
Zuck Small	2	0.60	27.51	0.79	**27.46**	0.74	30.21	0.49	**30.19**	0.44	**30.09**	0.53	30.32	0.28	**30.09**	0.44	30.25	0.46
		0.90	31.26	0.79	**31.21**	0.74	33.96	0.49	**33.94**	0.44	**33.84**	0.53	34.07	0.27	**33.84**	0.44	34.00	0.46
		0.99	35.05	0.79	**35.00**	0.73	37.75	0.49	**37.72**	0.43	**37.62**	0.53	37.86	0.27	**37.63**	0.43	37.78	0.46
	5	0.60	461.90	36.50	**29.28**	0.99	542.78	0.56	**30.26**	0.43	542.56	0.53	**32.96**	11.73	542.58	0.54	**30.24**	0.33
		0.90	463.85	36.29	**33.03**	0.99	544.28	0.56	**34.01**	0.42	544.06	0.53	**36.71**	11.70	544.08	0.54	**33.99**	0.33
		0.99	465.82	36.08	**36.82**	0.98	545.79	0.56	**37.81**	0.42	545.58	0.53	**40.50**	11.67	545.60	0.54	**37.78**	0.33
	10	0.60	611.91	27.70	**29.36**	0.47	702.66	0.46	**30.13**	0.20	702.78	0.41	**51.28**	25.98	697.27	20.59	**30.21**	0.23
		0.90	613.28	27.53	**33.08**	0.46	703.41	0.46	**33.85**	0.20	703.53	0.41	**54.94**	25.90	698.05	20.49	**33.94**	0.23
		0.99	614.67	27.36	**36.83**	0.46	704.17	0.46	**37.61**	0.20	704.29	0.41	**58.63**	25.83	698.83	20.40	**37.70**	0.23
	20	0.60	693.01	12.84	**30.20**	0.33	749.14	7.36	**30.58**	0.18	750.48	10.15	**155.03**	22.83	750.60	10.34	**30.59**	0.19
		0.90	694.07	12.77	**33.92**	0.33	749.69	7.32	**34.30**	0.18	751.03	10.11	**158.38**	22.75	751.15	10.29	**34.32**	0.19
		0.99	695.15	12.69	**37.68**	0.33	750.26	7.29	**38.06**	0.18	751.59	10.06	**161.77**	22.68	751.70	10.25	**38.07**	0.19
KD	2	0.60	111.05	6.99	**58.13**	0.62	237.34	0.10	**59.19**	0.20	237.38	0.08	**59.17**	0.21	237.35	0.10	**59.11**	0.13
		0.90	112.22	6.97	**59.39**	0.62	237.97	0.10	**60.45**	0.20	238.01	0.08	**60.43**	0.21	237.98	0.10	**60.37**	0.13
		0.99	113.39	6.96	**60.66**	0.62	238.60	0.10	**61.72**	0.20	238.64	0.08	**61.70**	0.21	238.61	0.10	**61.64**	0.13
	5	0.60	214.50	8.64	**61.55**	1.09	339.23	0.04	**59.84**	4.99	339.24	0.04	**60.41**	6.16	339.23	0.04	**58.22**	0.07
		0.90	215.42	8.62	**62.79**	1.08	339.48	0.04	**61.08**	4.98	339.49	0.04	**61.65**	6.15	339.48	0.04	**59.47**	0.07
		0.99	216.35	8.59	**64.03**	1.08	339.73	0.04	**62.34**	4.98	339.75	0.04	**62.91**	6.14	339.73	0.04	**60.73**	0.07
	10	0.60	277.33	13.36	**59.48**	0.57	375.85	0.03	**91.86**	22.47	375.85	0.03	**94.56**	18.56	375.84	0.03	**57.80**	0.10
		0.90	278.10	13.31	**60.72**	0.57	375.97	0.03	**93.04**	22.43	375.97	0.03	**95.74**	18.52	375.97	0.03	**59.05**	0.10
		0.99	278.88	13.26	**61.97**	0.57	376.10	0.03	**94.24**	22.38	376.10	0.03	**96.93**	18.48	376.10	0.03	**60.31**	0.10
	20	0.60	295.92	20.07	**60.05**	0.24	340.19	0.06	**131.94**	32.13	340.18	0.08	**134.66**	24.73	340.16	0.06	**59.18**	0.06
		0.90	296.64	20.02	**61.29**	0.24	340.44	0.06	**133.04**	32.06	340.43	0.08	**135.77**	24.68	340.41	0.06	**60.43**	0.06
		0.99	297.36	19.97	**62.55**	0.23	340.70	0.06	**134.16**	31.99	340.69	0.07	**136.88**	24.63	340.67	0.06	**61.69**	0.06
Zuck Medium	2	0.60	384.19	1.36	**85.43**	1.99	384.76	0.98	**86.44**	1.58	384.69	0.83	**88.11**	1.76	385.00	0.96	**86.49**	1.86
		0.90	385.41	1.35	**87.78**	1.98	385.98	0.98	**88.79**	1.58	385.92	0.83	**90.45**	1.76	386.21	0.95	**88.84**	1.85
		0.99	386.64	1.34	**90.15**	1.97	387.22	0.97	**91.16**	1.57	387.16	0.83	**92.82**	1.75	387.44	0.94	**91.22**	1.85
	5	0.60	585.00	0.47	**88.59**	1.05	586.37	0.44	**89.50**	1.20	586.51	0.44	**120.25**	54.00	586.28	0.53	**89.31**	1.10
		0.90	585.49	0.47	**90.97**	1.05	586.86	0.44	**91.88**	1.19	586.99	0.44	**122.52**	53.83	586.77	0.53	**91.68**	1.09
		0.99	585.98	0.47	**93.36**	1.04	587.35	0.43	**94.28**	1.19	587.49	0.44	**124.82**	53.67	587.26	0.53	**94.08**	1.09
	10	0.60	651.44	0.28	**87.20**	0.86	646.09	18.53	**87.03**	0.79	655.42	0.23	**242.69**	63.79	655.32	0.23	**86.70**	0.64
		0.90	651.69	0.28	**89.59**	0.85	646.36	18.46	**89.42**	0.78	655.66	0.23	**244.63**	63.59	655.57	0.23	**89.11**	0.64
		0.99	651.93	0.27	**92.01**	0.85	646.63	18.38	**91.83**	0.78	655.91	0.23	**246.58**	63.39	655.81	0.23	**91.54**	0.64
	20	0.60	686.75	0.29	**85.60**	0.56	653.99	7.83	**85.60**	0.58	652.19	10.35	**206.68**	33.66	652.15	10.46	**85.60**	0.48
		0.90	686.87	0.29	**88.01**	0.56	654.24	7.80	**88.02**	0.58	652.44	10.31	**208.75**	33.57	652.41	10.42	**88.01**	0.48
		0.99	686.99	0.29	**90.44**	0.55	654.50	7.76	**90.46**	0.58	652.70	10.27	**210.84**	33.47	652.67	10.38	**90.45**	0.48
P4HD	2	0.60	119.52	1.76	**59.72**	0.41	154.42	0.11	**60.01**	0.33	154.40	0.10	**60.10**	0.35	154.41	0.12	**59.98**	0.35
		0.90	120.12	1.75	**60.46**	0.41	154.80	0.11	**60.75**	0.33	154.78	0.10	**60.85**	0.35	154.78	0.12	**60.73**	0.35
		0.99	120.73	1.74	**61.22**	0.41	155.18	0.11	**61.50**	0.33	155.16	0.10	**61.60**	0.35	155.17	0.12	**61.48**	0.35
	5	0.60	164.13	2.55	**61.05**	2.98	213.16	0.06	**62.99**	4.25	213.14	0.05	**61.09**	2.16	213.15	0.05	**60.30**	0.25
		0.90	164.55	2.54	**61.78**	2.97	213.31	0.06	**63.72**	4.24	213.29	0.05	**61.82**	2.15	213.31	0.05	**61.04**	0.25
		0.99	164.98	2.53	**62.52**	2.96	213.46	0.06	**64.46**	4.23	213.44	0.05	**62.56**	2.15	213.46	0.05	**61.78**	0.25
	10	0.60	184.41	4.80	**63.75**	8.73	231.41	0.03	**62.59**	6.50	231.42	0.03	**77.95**	5.96	231.42	0.03	**60.27**	0.17
		0.90	184.78	4.78	**64.49**	8.71	231.49	0.03	**63.33**	6.48	231.50	0.03	**78.66**	5.95	231.49	0.03	**61.01**	0.17
		0.99	185.15	4.75	**65.23**	8.69	231.56	0.03	**64.08**	6.47	231.58	0.03	**79.37**	5.93	231.57	0.03	**61.76**	0.17
	20	0.60	173.62	3.84	**63.68**	5.21	222.90	0.10	**76.96**	10.17	222.87	0.09	**97.92**	10.67	222.86	0.10	**60.63**	0.11
		0.90	174.04	3.83	**64.42**	5.20	223.01	0.09	**77.68**	10.15	222.98	0.09	**98.59**	10.64	222.97	0.10	**61.38**	0.11
		0.99	174.47	3.82	**65.17**	5.19	223.12	0.09	**78.40**	10.12	223.10	0.09	**99.26**	10.61	223.09	0.10	**62.14**	0.11
Marvin	2	0.60	414.53	88.67	**44.21**	2.15	459.13	1.22	**47.53**	1.53	459.39	1.15	**48.65**	2.69	459.52	0.92	**47.23**	1.37
		0.90	417.20	87.96	**48.87**	2.14	461.45	1.22	**52.19**	1.52	461.71	1.14	**53.31**	2.67	461.84	0.91	**51.89**	1.36
		0.99	419.90	87.24	**53.57**	2.12	463.79	1.21	**56.89**	1.51	464.06	1.13	**58.01**	2.66	464.18	0.91	**56.60**	1.36
	5	0.60	579.89	87.70	**45.83**	1.36	709.64	4.46	**48.20**	0.88	539.71	1.56	**50.42**	1.38	711.03	4.50	**48.13**	0.85
		0.90	581.90	87.05	**50.44**	1.35	710.57	4.46	**52.80**	0.88	541.56	1.56	**55.01**	1.37	711.96	4.50	**52.73**	0.85
		0.99	583.93	86.39	**55.09**	1.35	711.51	4.46	**57.44**	0.87	543.42	1.55	**59.65**	1.36	712.89	4.50	**57.38**	0.85
	10	0.60	618.59	52.39	**45.88**	0.81	712.37	2.65	**47.86**	0.69	628.37	1.61	**112.78**	62.70	711.74	2.67	**48.03**	0.92
		0.90	620.61	52.10	**50.51**	0.80	713.29	2.65	**52.49**	0.69	629.76	1.61	**117.19**	62.48	712.67	2.67	**52.66**	0.92
		0.99	622.65	51.81	**55.19**	0.80	714.23	2.65	**57.17**	0.68	631.15	1.61	**121.64**	62.25	713.60	2.67	**57.33**	0.91
	20	0.60	694.70	45.21	**45.37**	0.67	792.82	1.86	**46.49**	0.63	635.30	2.31	**279.21**	79.79	792.60	1.73	**46.46**	0.49
		0.90	696.37	44.91	**50.00**	0.67	793.28	1.86	**51.12**	0.63	636.68	2.31	**283.10**	79.51	793.06	1.73	**51.09**	0.48
		0.99	698.04	44.61	**54.68**	0.67	793.75	1.86	**55.80**	0.63	638.07	2.31	**287.03**	79.22	793.53	1.73	**55.76**	0.48

tion budget of 10,000. Initial solutions are generated via a greedy–randomized heuristic and further improved using period-swap mutation with probability $P_m = 0.1$ [23].

We evaluate MOEA/D [24], NSGA-II [25], SMS-EMOA [26], and SPEA2 [27], extended with the proposed diversity-based change response (-DIV) and compared to re-evaluation baselines (-RE). MOEA/D uses neighborhood size 8, selection probability 0.9, and replaces up to 12 solutions per iteration. NSGA-II and SPEA2 use equal parent–offspring sizes, while SMS-EMOA generates one offspring per iteration.

TABLE III: Statistical comparison of total offline error. $X^{(+)}$ indicates the column algorithm is significantly worse than X, $X^{(-)}$ indicates it is significantly better, and $X^{(*)}$ denotes no significant difference.

Inst.	ν	α	MOEA/D-RE(1)	MOEA/D-DIV(2)	NSGA-II-RE(3)	NSGA-II-DIV(4)	SPEA2-RE(5)	SPEA2-DIV(6)	SMS-EMOA-RE(7)	SMS-EMOA-DIV(8)
Newman1	2	0.60	$2^+3^-4^+5^*6^+7^-8^*$	$1^-3^-4^*5^-6^-7^-8^-$	$1^+2^+4^+5^*6^+7^*8^+$	$1^-2^*3^-5^-6^*7^-8^*$	$1^*2^+3^*4^+6^+7^*8^+$	$1^-2^+3^-4^*5^-7^-8^*$	$1^+2^+3^*4^+5^*6^+8^+$	$1^*2^+3^-4^*5^-6^*7^-$
		0.90	$2^+3^-4^+5^*6^+7^-8^*$	$1^-3^-4^*5^-6^-7^-8^-$	$1^+2^+4^+5^*6^+7^*8^+$	$1^-2^*3^-5^-6^*7^-8^*$	$1^*2^+3^*4^+6^+7^*8^+$	$1^-2^+3^-4^*5^-7^-8^*$	$1^+2^+3^*4^+5^*6^+8^+$	$1^*2^+3^-4^*5^-6^*7^-$
		0.99	$2^+3^-4^+5^*6^+7^-8^*$	$1^-3^-4^*5^-6^-7^-8^-$	$1^+2^+4^+5^*6^+7^*8^+$	$1^-2^*3^-5^-6^*7^-8^*$	$1^*2^+3^*4^+6^+7^*8^+$	$1^-2^+3^-4^*5^-7^-8^*$	$1^+2^+3^*4^+5^*6^+8^+$	$1^*2^+3^-4^*5^-6^*7^-$
	5	0.60	$2^+3^*4^+5^*6^+7^-8^*$	$1^-3^-4^-5^-6^*7^-8^-$	$1^*2^+4^+5^*6^+7^*8^+$	$1^-2^+3^-5^-6^*7^-8^*$	$1^*2^+3^*4^+6^+7^*8^+$	$1^-2^*3^-4^*5^-7^-8^*$	$1^+2^+3^*4^+5^*6^+8^+$	$1^*2^+3^-4^*5^-6^*7^-$
		0.90	$2^+3^*4^+5^*6^+7^-8^*$	$1^-3^-4^-5^-6^*7^-8^-$	$1^*2^+4^+5^*6^+7^*8^+$	$1^-2^+3^-5^-6^*7^-8^*$	$1^*2^+3^*4^+6^+7^*8^+$	$1^-2^*3^-4^*5^-7^-8^*$	$1^+2^+3^*4^+5^*6^+8^+$	$1^*2^+3^-4^*5^-6^*7^-$
		0.99	$2^+3^*4^+5^*6^+7^-8^*$	$1^-3^-4^-5^-6^*7^-8^-$	$1^*2^+4^+5^*6^+7^*8^+$	$1^-2^+3^-5^-6^*7^-8^*$	$1^*2^+3^*4^+6^+7^*8^+$	$1^-2^*3^-4^*5^-7^-8^*$	$1^+2^+3^*4^+5^*6^+8^+$	$1^*2^+3^-4^*5^-6^*7^-$
	10	0.60	$2^+3^*4^+5^*6^+7^*8^+$	$1^-3^-4^*5^-6^*7^-8^-$	$1^*2^+4^+5^*6^+7^-8^+$	$1^-2^*3^-5^-6^*7^-8^*$	$1^*2^+3^*4^+6^+7^-8^*$	$1^-2^*3^-4^*5^-7^-8^*$	$1^*2^+3^+4^+5^+6^+8^+$	$1^-2^+3^-4^*5^*6^*7^-$
		0.90	$2^+3^*4^+5^*6^+7^*8^+$	$1^-3^-4^*5^-6^*7^-8^-$	$1^*2^+4^+5^*6^+7^-8^*$	$1^-2^*3^-5^-6^*7^-8^*$	$1^*2^+3^*4^+6^+7^-8^*$	$1^-2^*3^-4^*5^-7^-8^*$	$1^*2^+3^+4^+5^+6^+8^+$	$1^-2^+3^*4^*5^*6^*7^-$
		0.99	$2^+3^*4^+5^*6^+7^*8^+$	$1^-3^-4^*5^-6^*7^-8^-$	$1^*2^+4^+5^*6^+7^-8^*$	$1^-2^*3^-5^-6^*7^-8^*$	$1^*2^+3^*4^+6^+7^-8^*$	$1^-2^*3^-4^*5^-7^-8^*$	$1^*2^+3^+4^+5^+6^+8^+$	$1^-2^+3^*4^*5^*6^*7^-$
	20	0.60	$2^+3^+4^+5^+6^+7^*8^+$	$1^-3^-4^*5^-6^*7^-8^-$	$1^-2^+4^+5^*6^+7^*8^*$	$1^-2^*3^-5^-6^*7^-8^*$	$1^-2^+3^*4^+6^+7^*8^*$	$1^-2^*3^-4^*5^-7^-8^*$	$1^*2^+3^*4^+5^*6^+8^+$	$1^-2^+3^*4^*5^*6^*7^-$
		0.90	$2^+3^+4^+5^+6^+7^*8^+$	$1^-3^-4^*5^-6^*7^-8^-$	$1^-2^+4^+5^*6^+7^*8^*$	$1^-2^*3^-5^-6^*7^-8^*$	$1^-2^+3^*4^+6^+7^*8^*$	$1^-2^*3^-4^*5^-7^-8^*$	$1^*2^+3^*4^+5^*6^+8^+$	$1^-2^+3^*4^*5^*6^*7^-$
		0.99	$2^+3^+4^+5^+6^+7^*8^+$	$1^-3^-4^*5^-6^*7^-8^-$	$1^-2^+4^+5^*6^+7^*8^*$	$1^-2^*3^-5^-6^*7^-8^*$	$1^-2^+3^*4^+6^+7^*8^*$	$1^-2^*3^-4^*5^-7^-8^*$	$1^*2^+3^*4^+5^*6^+8^+$	$1^-2^+3^*4^*5^*6^*7^-$
P4HD	2	0.60	$2^-3^-4^-5^+6^+7^+8^+$	$1^-2^-3^-4^-5^*7^*8^*$	$1^+3^*4^*5^+6^+7^+8^+$	$1^-2^-3^-4^-5^*6^*8^*$	$1^+2^*4^*5^+6^+7^+8^+$	$1^-2^-3^-4^-6^*7^*8^*$	$1^+2^*3^*5^+6^+7^+8^+$	$1^-2^-3^-4^-5^*6^*7^*$
		0.90	$2^-3^-4^-5^+6^+7^+8^+$	$1^-2^-3^-4^-5^*7^*8^*$	$1^+3^*4^*5^+6^+7^+8^+$	$1^-2^-3^-4^-5^*6^*8^*$	$1^+2^*4^*5^+6^+7^+8^+$	$1^-2^-3^-4^-6^*7^*8^*$	$1^+2^*3^*5^+6^+7^+8^+$	$1^-2^-3^-4^-5^*6^*7^*$
		0.99	$2^-3^-4^-5^+6^+7^+8^+$	$1^-2^-3^-4^-5^*7^*8^*$	$1^+3^*4^*5^+6^+7^+8^+$	$1^-2^-3^-4^-5^*6^*8^*$	$1^+2^*4^*5^+6^+7^+8^+$	$1^-2^-3^-4^-6^*7^*8^*$	$1^+2^*3^*5^+6^+7^+8^+$	$1^-2^-3^-4^-5^*6^*7^*$
	5	0.60	$2^-3^*4^-5^+6^+7^*8^+$	$1^-2^-3^-4^-5^*7^*8^*$	$1^+3^*4^*5^+6^+7^+8^+$	$1^*2^-3^-4^-5^*6^*8^*$	$1^*2^*4^*5^+6^+7^+8^+$	$1^-2^-3^-4^-6^*7^*8^*$	$1^+2^*3^*5^+6^+7^+8^+$	$1^-2^-3^-4^-5^*6^*7^*$
		0.90	$2^-3^*4^-5^+6^+7^*8^+$	$1^-2^-3^-4^-5^*7^*8^*$	$1^+3^*4^*5^+6^+7^+8^+$	$1^*2^-3^-4^-5^*6^*8^*$	$1^*2^*4^*5^+6^+7^+8^+$	$1^-2^-3^-4^-6^*7^*8^*$	$1^+2^*3^*5^+6^+7^+8^+$	$1^-2^-3^-4^-5^*6^*7^*$
		0.99	$2^-3^*4^-5^+6^+7^*8^+$	$1^-2^-3^-4^-5^*7^*8^*$	$1^+3^*4^*5^+6^+7^+8^+$	$1^*2^-3^-4^-5^*6^*8^*$	$1^*2^*4^*5^+6^+7^+8^+$	$1^-2^-3^-4^-6^*7^*8^*$	$1^+2^*3^*5^+6^+7^+8^+$	$1^-2^-3^-4^-5^*6^*7^*$
	10	0.60	$2^*3^-4^-5^*6^+7^+8^+$	$1^-2^-3^-4^-5^*7^*8^*$	$1^*3^*4^*5^+6^+7^+8^+$	$1^-2^-3^-4^-5^*6^*8^*$	$1^+2^*4^*5^+6^+7^+8^+$	$1^*2^-3^-4^-6^*7^*8^+$	$1^+2^*3^*5^+6^+7^+8^+$	$1^-2^-3^-4^-5^-6^*7^*$
		0.90	$2^*3^-4^-5^*6^+7^+8^+$	$1^-2^-3^-4^-5^*7^*8^*$	$1^*3^*4^*5^+6^+7^+8^+$	$1^-2^-3^-4^-5^*6^*8^*$	$1^+2^*4^*5^+6^+7^+8^+$	$1^*2^-3^-4^-6^*7^*8^+$	$1^+2^*3^*5^+6^+7^+8^+$	$1^-2^-3^-4^-5^-6^*7^*$
		0.99	$2^*3^-4^-5^*6^+7^+8^+$	$1^-2^-3^-4^-5^*7^*8^*$	$1^*3^*4^*5^+6^+7^+8^+$	$1^-2^-3^-4^-5^*6^*8^*$	$1^+2^*4^*5^+6^+7^+8^+$	$1^*2^-3^-4^-6^*7^*8^+$	$1^+2^*3^*5^+6^+7^+8^+$	$1^-2^-3^-4^-5^-6^*7^*$
	20	0.60	$2^-3^-4^*5^*6^+7^+8^+$	$1^-2^-3^-4^-5^-7^*8^*$	$1^+3^*4^*5^+6^+7^+8^+$	$1^-2^-3^-4^-5^*6^*8^*$	$1^+2^*4^*5^+6^+7^+8^+$	$1^*2^-3^-4^-6^+7^*8^+$	$1^*2^*3^*5^+6^+7^+8^+$	$1^-2^-3^-4^-5^-6^*7^*$
		0.90	$2^-3^-4^*5^*6^+7^+8^+$	$1^-2^-3^-4^-5^-7^*8^*$	$1^+3^*4^*5^+6^+7^+8^+$	$1^-2^-3^-4^-5^*6^*8^*$	$1^+2^*4^*5^+6^+7^+8^+$	$1^*2^-3^-4^-6^+7^*8^+$	$1^*2^*3^*5^+6^+7^+8^+$	$1^-2^-3^-4^-5^-6^*7^*$
		0.99	$2^-3^-4^*5^*6^+7^+8^+$	$1^-2^-3^-4^-5^-7^*8^*$	$1^+3^*4^*5^+6^+7^+8^+$	$1^-2^-3^-4^-5^*6^*8^*$	$1^+2^*4^*5^+6^+7^+8^+$	$1^*2^-3^-4^-6^+7^*8^+$	$1^*2^*3^*5^+6^+7^+8^+$	$1^-2^-3^-4^-5^-6^*7^*$
Marvin	2	0.60	$2^+3^*4^+5^*6^+7^*8^+$	$1^-3^-4^*5^-6^*7^-8^*$	$1^*2^+4^+5^*6^+7^*8^+$	$1^-2^*3^-5^-6^*7^-8^*$	$1^*2^+3^*4^+6^+7^*8^+$	$1^-2^*3^-4^*5^-7^-8^*$	$1^*2^+3^*4^+5^*6^+8^+$	$1^-2^*3^-4^*5^-6^*7^-$
		0.90	$2^+3^*4^+5^*6^+7^*8^+$	$1^-3^-4^*5^-6^*7^-8^*$	$1^*2^+4^+5^*6^+7^*8^+$	$1^-2^*3^-5^-6^*7^-8^*$	$1^*2^+3^*4^+6^+7^*8^+$	$1^-2^*3^-4^*5^-7^-8^*$	$1^*2^+3^*4^+5^*6^+8^+$	$1^-2^*3^-4^*5^-6^*7^-$
		0.99	$2^+3^*4^+5^*6^+7^*8^+$	$1^-3^-4^*5^-6^*7^-8^*$	$1^*2^+4^+5^*6^+7^*8^+$	$1^-2^*3^-5^-6^*7^-8^*$	$1^*2^+3^*4^+6^+7^*8^+$	$1^-2^*3^-4^*5^-7^-8^*$	$1^*2^+3^*4^+5^*6^+8^+$	$1^-2^*3^-4^*5^-6^*7^-$
	5	0.60	$2^+3^*4^+5^*6^+7^*8^+$	$1^-3^-4^*5^-6^*7^-8^-$	$1^*2^+4^+5^*6^+7^+8^+$	$1^-2^*3^-5^-6^*7^-8^*$	$1^*2^+3^*4^+6^+7^+8^+$	$1^-2^*3^-4^*5^-7^-8^*$	$1^*2^+3^-4^+5^-6^+8^*$	$1^-2^+3^-4^*5^-6^*7^*$
		0.90	$2^+3^*4^+5^*6^+7^*8^+$	$1^-3^-4^*5^-6^*7^-8^-$	$1^*2^+4^+5^*6^+7^+8^+$	$1^-2^*3^-5^-6^*7^-8^*$	$1^*2^+3^*4^+6^+7^+8^+$	$1^-2^*3^-4^*5^-7^-8^*$	$1^*2^+3^-4^+5^-6^+8^*$	$1^-2^+3^-4^*5^-6^*7^*$
		0.99	$2^+3^*4^+5^*6^+7^*8^+$	$1^-3^-4^*5^-6^*7^-8^-$	$1^*2^+4^+5^*6^+7^+8^+$	$1^-2^*3^-5^-6^*7^-8^*$	$1^*2^+3^*4^+6^+7^+8^+$	$1^-2^*3^-4^*5^-7^-8^*$	$1^*2^+3^-4^+5^-6^+8^*$	$1^-2^+3^-4^*5^-6^*7^*$
	10	0.60	$2^+3^-4^+5^*6^+7^*8^*$	$1^-3^-4^*5^-6^*7^-8^-$	$1^+2^+4^+5^*6^+7^*8^+$	$1^-2^*3^-5^-6^*7^-8^*$	$1^*2^+3^*4^+6^+7^*8^+$	$1^-2^*3^-4^*5^-7^-8^*$	$1^*2^+3^-4^+5^*6^+8^*$	$1^*2^+3^-4^*5^-6^*7^*$
		0.90	$2^+3^-4^+5^*6^+7^*8^*$	$1^-3^-4^*5^-6^*7^-8^-$	$1^+2^+4^+5^*6^+7^+8^+$	$1^-2^*3^-5^-6^*7^-8^*$	$1^*2^+3^*4^+6^+7^*8^+$	$1^-2^*3^-4^*5^-7^-8^*$	$1^*2^+3^-4^+5^*6^+8^*$	$1^*2^+3^-4^*5^-6^*7^*$
		0.99	$2^+3^-4^+5^*6^+7^*8^*$	$1^-3^-4^*5^-6^*7^-8^-$	$1^+2^+4^+5^*6^+7^+8^+$	$1^-2^*3^-5^-6^*7^-8^*$	$1^*2^+3^*4^+6^+7^*8^+$	$1^-2^*3^-4^*5^-7^-8^*$	$1^*2^+3^-4^+5^*6^+8^*$	$1^*2^+3^-4^*5^-6^*7^*$
	20	0.60	$2^+3^*4^+5^*6^+7^*8^+$	$1^-3^-4^*5^-6^*7^-8^-$	$1^*2^+4^+5^*6^+7^+8^+$	$1^-2^*3^-5^-6^*7^-8^*$	$1^*2^+3^*4^+6^+7^+8^+$	$1^-2^*3^-4^*5^-7^-8^*$	$1^*2^+3^-4^+5^-6^+8^*$	$1^-2^+3^-4^*5^-6^*7^*$
		0.90	$2^+3^*4^+5^*6^+7^*8^+$	$1^-3^-4^*5^-6^*7^-8^-$	$1^*2^+4^+5^*6^+7^+8^+$	$1^-2^*3^-5^-6^*7^-8^*$	$1^*2^+3^*4^+6^+7^+8^+$	$1^-2^*3^-4^*5^-7^-8^*$	$1^*2^+3^-4^+5^-6^+8^*$	$1^-2^+3^-4^*5^-6^*7^*$
		0.99	$2^+3^*4^+5^*6^+7^*8^+$	$1^-3^-4^*5^-6^*7^-8^-$	$1^*2^+4^+5^*6^+7^+8^+$	$1^-2^*3^-5^-6^*7^-8^*$	$1^*2^+3^*4^+6^+7^+8^+$	$1^-2^*3^-4^*5^-7^-8^*$	$1^*2^+3^-4^+5^-6^+8^*$	$1^-2^+3^-4^*5^-6^*7^*$

Performance is measured using offline error relative to the deterministic upper bound $p(x^*)$, obtained using Gurobi. For each change i, $e_i = p(x^*) - p(x_i)$ if feasible, and $e_i = p(x^*) + v(x_i)$ otherwise. The overall error is $E = \frac{1}{\nu}\sum_{i=1}^{\nu} e_i$. Statistical significance is assessed using the Kruskal–Wallis test with 95% confidence and Bonferroni correction [28].

IV. Experimental Results

This section evaluates the proposed change response mechanism on the DCC-OPMSP against re-evaluation baselines. Tables II and III present the mean, standard deviation, and statistical comparisons of offline error across different mining instances under stochastic and dynamic settings.

Lower offline error values indicate better performance, corresponding to solutions with profits closer to the optimal value. Across all instances and settings, the –DIV variants consistently achieve significantly lower offline error than their –RE counterparts, demonstrating improved adaptability to dynamic changes. The performance gap is particularly pronounced in several instances, where re-evaluation methods produce significantly higher offline error, indicating difficulty in recovering feasibility after changes.

As the confidence level α increases, the offline error also increases. Higher confidence levels impose stricter feasibility requirements, resulting in more risk-averse extraction sequences and lower achievable profits.

Additionally, offline error decreases as the number of dynamic changes ν decreases, since less frequent changes allow more time for adaptation and convergence. When $\nu = 20$, MOEA/D-DIV outperforms other algorithms with a diversity-based mechanism for all the mining instances, while SPEA2-DIV underperforms other -DIV algorithms. However, when $\nu = 2$, almost all the -DIV variants perform similarly. In this setting, MOEA/D-RE also performs similarly to MOEA/D-DIV for the Zuck Small instance.

Table III further confirms that the –DIV variants significantly outperform their corresponding –RE baselines across most instances and settings, with consistent trends observed across all mining instances.

Our results indicate that the diversity-based method significantly outperforms the corresponding re-evaluation–based baselines across different frequencies of dynamic changes and confidence levels in mining instances with up to $53{,}271$ blocks. Moreover, the proposed bi-objective formulation produces a set of solutions for any confidence level within the considered range in a single run. Overall, these findings demonstrate that the proposed bi-objective formulation and the dynamic diversity-based change response mechanism are well-suited for large-scale open-pit mine scheduling in stochastic and dynamic environments.

V. Conclusion

In this paper, we study a dynamic chance-constrained approach for the open-pit mine scheduling problem with stochastic economic values and time-varying resource capacities. The problem is formulated as a bi-objective optimization model that maximizes expected NPV and minimizes its standard deviation, enabling risk-aware planning. Unlike traditional approaches requiring a fixed confidence level, the proposed formulation produces a Pareto front capturing multiple confidence levels in a single run. To handle dynamic changes, we employ a diversity-based change-response mechanism that combines solution repair with randomly generated feasible solutions. The approach is evaluated against re-evaluation baselines using four MOEAs. Results show that the proposed variants consistently outperform the baselines across all instances and settings, with MOEA/D-DIV and SMS-EMOA-DIV achieving the best performance. Overall, the proposed approach effectively handles stochastic and dynamic variations while producing high-quality, risk-aware schedules.

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References

[1] O. Rivera-Letelier, D. Espinoza, M. Goycoolea, E. Moreno, and G. Muñoz, "Production scheduling for strategic open pit mine planning: a mixed-integer programming approach," *Oper. Res.*, 2020.

[2] E. Jélvez, N. Morales, P. Nancel-Penard, J. Peypouquet, and P. Reyes, "Aggregation heuristic for the open-pit block scheduling problem," *Eur. J. Oper. Res.*, 2016.

[3] S. Elsayed, R. Sarker, D. Essam, and C. A. Coello Coello, "Evolutionary approach for large-scale mine scheduling," *Inf. Sci.*, 2020.

[4] I. H. Pathiranage and A. Neumann, "Multi-objective evolutionary optimization for large-scale open pit mine scheduling," in *IEEE CEC 2024*. IEEE, 2024.

[5] S. Chatterjee and R. Dimitrakopoulos, "Production scheduling under uncertainty of an open-pit mine using lagrangian relaxation and branch-and-cut algorithm," *Int. J. Min. Reclam. Environ.*, 2020.

[6] A. Khan and C. Niemann-Delius, "A differential evolution based approach for the production scheduling of open pit mines with or without the condition of grade uncertainty," *Appl. Soft Comput.*, 2018.

[7] M. Stimson, W. Reid, A. Neumann, S. Ratcliffe, and F. Neumann, "Improving confidence in evolutionary mine scheduling via uncertainty discounting," in *IEEE CEC 2023*. IEEE, 2023.

[8] A. Paithankar and S. Chatterjee, "Open pit mine production schedule optimization using a hybrid of maximum-flow and genetic algorithms," *Appl. Soft Comput.*, 2019.

[9] H. Assimi, O. Harper, Y. Xie, A. Neumann, and F. Neumann, "Evolutionary bi-objective optimization for the dynamic chance-constrained knapsack problem based on tail bound objectives," in *ECAI 2020*. IOS Press, 2020.

[10] I. H. Pathiranage, F. Neumann, D. Antipov, and A. Neumann, "Using 3-objective evolutionary algorithms for the dynamic chance constrained knapsack problem," in *GECCO 2024*. ACM, 2024.

[11] K. K. Perera and A. Neumann, "Multi-objective evolutionary algorithms with sliding window selection for the dynamic chance-constrained knapsack problem," in *GECCO 2024*. ACM, 2024.

[12] A. Charnes and W. W. Cooper, "Chance-constrained programming," *Manage. Sci.*, 1959.

[13] W. Reid, A. Neumann, S. Ratcliffe, and F. Neumann, "Advanced mine optimisation under uncertainty using evolution," in *GECCO 2021*. ACM, 2021.

[14] X. Yan, A. Neumann, and F. Neumann, "Sliding window bi-objective evolutionary algorithms for optimizing chance-constrained monotone submodular functions," in *PPSN 2024*. Springer, 2024.

[15] A. Neumann and F. Neumann, "Optimizing monotone chance-constrained submodular functions using evolutionary multiobjective algorithms," *Evol. Comput.*, 2025.

[16] I. Hewa Pathiranage, F. Neumann, D. Antipov, and A. Neumann, "Effective 2- and 3-objective MOEA/D approaches for the chance constrained knapsack problem," in *GECCO 2024*. ACM, 2024.

[17] K. K. Perera, F. Neumann, and A. Neumann, "Multi-objective evolutionary approaches for the knapsack problem with stochastic profits," in *PPSN 2024*. Springer, 2024.

[18] K. Deb, U. B. Rao N., and S. Karthik, "Dynamic multi-objective optimization and decision-making using modified NSGA-II: A case study on hydro-thermal power scheduling," in *EMO 2007*. Springer, 2007.

[19] I. H. Pathiranage and A. Neumann, "On the use of bi-objective evolutionary algorithms for the stochastic multiple knapsack problem under dynamic constraints," in *GECCO 2026*. ACM, 2026, to appear.

[20] D. Espinoza, M. Goycoolea, E. Moreno, and A. Newman, "Minelib: A library of open pit mining problems," *Ann. Oper. Res.*, 2013.

[21] A. Neumann, Y. Xie, and F. Neumann, "Evolutionary algorithms for limiting the effect of uncertainty for the knapsack problem with stochastic profits," in *PPSN 2022*. Springer, 2022.

[22] S. Jiang, J. Zou, S. Yang, and X. Yao, "Evolutionary dynamic multi-objective optimisation: A survey," *ACM Comput. Surv.*, 2022.

[23] I. H. Pathiranage and A. Neumann, "Bi-objective evolutionary optimization for large-scale open pit mine scheduling problem under uncertainty with chance constraints," *arXiv, 2511.08275*, 2025.

[24] Q. Zhang and H. Li, "MOEA/D: A multiobjective evolutionary algorithm based on decomposition," *IEEE Trans. Evol. Comput.*, 2007.

[25] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Trans. Evol. Comput.*, 2002.

[26] N. Beume, B. Naujoks, and M. Emmerich, "SMS-EMOA: Multiobjective selection based on dominated hypervolume," *Eur. J. Oper. Res.*, 2007.

[27] E. Zitzler, M. Laumanns, and L. Thiele, "SPEA2: Improving the strength pareto evolutionary algorithm," *TIK report*, 2001.

[28] G. W. Corder and D. I. Foreman, *Nonparametric statistics for non-statisticians: A step-by-step approach*. John Wiley & Sons, 2014.