The Effect of Epigenetic Blocking on Dynamic Multi-Objective Optimisation Problems

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ABSTRACT
Hundreds of Evolutionary Computation approaches have been reported. From an evolutionary perspective they focus on two fundamental mechanisms: cultural inheritance in Swarm Intelligence and genetic inheritance in Evolutionary Algorithms. Contemporary evolutionary biology looks beyond genetic inheritance, proposing a so-called “Extended Evolutionary Synthesis”. Many concepts from the Extended Evolutionary Synthesis have been left out of Evolutionary Computation as interest has moved towards specific implementations of the same general mechanisms. One such concept is epigenetic inheritance, which is increasingly considered central to evolutionary thinking. Epigenetic mechanisms allow quick non- or partially-genetic adaptations to environmental changes. Dynamic multi-objective optimisation problems represent similar circumstances to the natural world where fitness can be determined by multiple objectives (traits), and the environment is constantly changing.

This paper asks if the advantages that epigenetic inheritance provide in the natural world are replicated in dynamic multi-objective optimisation problems. Specifically, an epigenetic blocking mechanism is applied to a state-of-the-art multi-objective genetic algorithm, MOEA/D-DE, and its performance is compared on three sets of dynamic test functions, FDA, JY, and UDE. The mechanism shows improved performance on 12 of the 16 test problems, providing initial evidence that more algorithms should explore the wealth of epigenetic mechanisms seen in the natural world.

CCS CONCEPTS
- Theory of computation → Evolutionary algorithms;  
- Computing methodologies → Genetic algorithms.

KEYWORDS
Genetic algorithms, multi-objective optimisation, dynamic optimisation, epigenetics

1 BORROWING FROM THE EXTENDED EVOLUTIONARY SYNTHESIS
The Modern Synthesis [11], a combination of Darwin and Wallace’s ideas of natural selection [5, 6], and Mendel’s principles of inheritance [1], has been an important inspiration for the concepts used in Evolutionary Algorithms. Despite the number of approaches available, the core inspiration is often just genetic inheritance. However, modern evolutionary theory has since continued to explore the mechanisms of evolution, extending the Modern Synthesis to include concepts of non-genetic inheritance such as epigenetics, parent effects, multilevel selection, and cultural inheritance in a portfolio proposed as the Extended Evolutionary Synthesis [16, 17].

Epigenetic mechanisms in evolutionary theory alter DNA expression, leading to a change in phenotype without a change in the underlying genotype [8]. This “phenotypic plasticity” leads to a faster rate of change to quickly adapt to changes in the environment, and the ability to revert changes if the environmental conditions do not activate the epigenetic mechanism. This is to allow adaptation to a natural world that is changing, optimising organisational fitness without altering its underlying genotype. Dynamic problems reflect a similar set of challenges by changing the optimal Pareto set or Pareto front over time [9]. This paper therefore explores if, and, if so, how epigenetics might be used within Evolutionary Algorithms to improve performance. Due to the faster-than-generational adaptation capabilities of epigenetics, these are first explored in a dynamic multi-objective problem context.

There is limited literature exploring epigenetic mechanisms in genetic algorithms; those that exist are focused on static single-objective problems. Results are nevertheless consistent with expectations based on evolutionary theory. The Knapsack problem was used to determine the performance of the cytosine methylation epigenetic process when added to a traditional genetic algorithm [4], resulting in a 25-30% reduction in the number of generations needed to reach an optimal solution. A constant probability of methylation is used, so the rate at which genes are blocked do not react to dynamic changes based on external factors or progression of the search. In epigenetic models, constant rates of variation are non-specific to the environment and act similar to mutation, while varying rates are directed by environmental cues [12].
2 EPGENETIC BLOCKING MECHANISM

There are three forms of epigenetic transfer possible: mitotic, germline, and experience-dependent [3, 21]. Germline and experience-dependent transfer passes down epigenetic marks that direct the epigenetic process for future generations, while mitotic transfer only propagates changes in the same generation. For an initial exploration of epigenetic mechanisms, a simple form of genetic blocking is chosen for inspiration based on mitotic transfer. A probabilistic blocking mechanism is used to block some variables in each individual from being changed during crossover. The parameters of the epigenetic process are not inherited across multiple generations (Figure 1).

A simple mechanism allows the properties to be analysed and to more clearly understand the effect of an epigenetic process on the performance of an algorithm. The simplicity also allows the mechanism to be adapted to any Evolutionary Algorithm by altering the crossover method without adding complicated features.

The mechanism has a probability to trigger during the reproduction stage for every parent without bias towards fitness as blocking both the fitter and less-fit parents have merits. Blocking fitter parents reduces stagnation of the population, i.e. maintains diversity, should the variables or objectives of the dynamic problem changes, while blocking less fit parents increases the convergence of the population through more rapid selection at the variable level.

By varying the probability and the number of genes that are blocked, and controlling the duration of each dynamic cycle in a problem, the impact of epigenetic blocking can be analysed and compared to a baseline algorithm, and to a constant probability of triggering the mechanism.

3 EXPERIMENTAL SETUP

The MOEA/D-DE algorithm [15] with the re-initialisation strategy outlined in [2] was chosen as the base algorithm for benchmarking due to its strong performance on dynamic optimisation problems. The fast converging nature of MOEA/D lets it adapt quickly in changing environments [14]. A population size of 500 is used.

Three variants of the epigenetic blocking mechanism are investigated by changing two parameters: the probability for the mechanism to trigger, and the number of variables blocked in the process (block size). A summary of the three variants is as follows:

- **E** - with a constant probability of 0.1 and a constant block size of 6.
- **EIB** - with a constant probability of 0.1 and a varying block size from 1 up to the number of variables in the problem.
- **EIP** - with a varying probability from 0 up to a maximum of 0.8 with a constant block size.

The gradual increase in either probability or block size is intended to increase the convergence of the population, as blocking more prevents diverse changes. The maximum probability is limited to 0.8 to prevent stagnation where the blocking occurs too often. Increases to probability are rounded to 0.01, increasing every 2 generations to the maximum probability. The block size increases are rounded to the nearest whole number and depends on the number of variables. For example, a problem with 30 variables and a population of 500 will increase the block size every 4 generations.

Details of these hyperparameters are shown in Table 1. $P(b)$ is the probability for the mechanism to trigger and $s$ is the block size. The Inverted Generational Distance (IGD) [19] metric is used to show the performance of the epigenetic variants to the MOEA/D-DE algorithm.

The FDA [9], JY [14], and UDF [2] benchmark functions are chosen to test the performance of the epigenetic blocking mechanism. The FDA and UDF functions are considered to be simpler to solve as they are based on the multi-objective ZDT [7] problems while the JY problems are more complex [13], including elements such as linkage between variables and multiple knee points. For the benchmark problem properties, $\tau$ is set at 5 and $n\tau$ at 10. This gives 5 generations before the problem changes and 10 distinct steps. In total this gives 100 generations (50,000 iterations) to complete a full cycle back to the original variables and objectives of the problem. 2 full cycles are benchmarked with 20 independent runs for analysis.

4 PERFORMANCE ON DYNAMIC MULTI-OBJECTIVE OPTIMISATION PROBLEMS

To determine how the changes in the block rate and the probability of change affect the performance, the three variants are compared by taking the average IGD every generation to match the rate at which the probability varies. The difference between each variant and the baseline are then compared to demonstrate the improvement in performance.

4.1 Performance of epigenetic approaches against each other

The total percentage difference between the baseline and each variant are summarised in Table 2. Positive values represent the epigenetic mechanism performing better than the baseline algorithm and negative values a decrease. Values highlighted have a p-value lower than 0.05 from a Wilcoxon signed-rank test and are statistically significant at the 95% level.

![Figure 1: The blocking mechanism where some variables are blocked from carrying over to the next generation.](image-url)
Table 2: The total % difference for a two full dynamic cycles. The \( p \)-values from a Wilcoxon signed-rank test is shown in brackets, bold indicates the best performing variant. The lighter blue boxes indicate an improvement in performance; darker red boxes indicate a decrease.

| Problem | E         | EIB        | EIP         |
|---------|-----------|------------|-------------|
| FDA1    | -102 (0.000) | -14 (0.027) | -188 (0.015) |
| FDA2    | 399 (0.000)  | 400 (0.000) | 316 (0.000)  |
| FDA3    | 163 (0.000)  | 189 (0.016) | 810 (0.000)  |
| JY1     | 657 (0.000)  | 504 (0.000) | 917 (0.000)  |
| JY2     | 193 (0.012)  | 41 (0.783)   | 470 (0.000)  |
| JY3     | 669 (0.000)  | 1164 (0.000) | 422 (0.000)  |
| JY5     | -231 (0.000) | -28 (0.518)  | 226 (0.002)  |
| JY6     | -19 (0.209)  | -15 (0.164)  | -30 (0.020)  |
| JY7     | 96 (0.871)   | 318 (0.029)  | 391 (0.001)  |
| JY8     | 16 (0.108)   | 29 (0.028)   | 37 (0.001)   |
| UDF1    | -181 (0.031) | 170 (0.013)  | -35 (0.687)  |
| UDF2    | -52 (0.323)  | 15 (0.728)   | -40 (0.024)  |
| UDF3    | 61 (0.000)   | -17 (0.000)  | 35 (0.586)   |
| UDF4    | 124 (0.003)  | 413 (0.000)  | -71 (0.027)  |
| UDF5    | -2 (0.217)   | 122 (0.262)  | -120 (0.287) |
| UDF6    | 206 (0.000)  | 180 (0.000)  | 128 (0.000)  |

The performance summary of the three variants is as follows:

- **E**: Positive performance on 8 out of 16 problems, best on 2 problems.
- **EIB**: Positive performance on 10 out of 16 problems, best on 4 problems.
- **EIP**: Positive performance on 9 out of 16 problems, best on 6 problems.

The presence of epigenetic blocking generally improves the performance compared to the baseline. It is only the FDA1 case where all of the epigenetic enhanced algorithms struggle. Both EIB and EIP generally outperform the E variant, where the blocking rate and probability of blocking remain static. This is expected as using a constant probability and block size does not allow the mechanism to react dynamically to changes in the problem.

EIP performs best on the most problems, 6, with 5 of these 6 problems in the JY problem set. The performance suggests that EIP works best on more complex problems with its aggressive use of the epigenetic mechanic compared to EIB and E. However, EIP doesn’t perform well on the UDF problem set, considered to be the simplest problems that are usually dominated by convergence, with 3 non-detectable results and 2 negative results where it performs worse. The aggressive behaviour of this variant leads to larger positive and negative results making it less robust.

In comparison, the EIB variant shows more consistency across the problem sets with only 1 significant negative result and is able to achieve a best result on each problem set. Although EIP can find stronger positive results in some problems, its inconsistency and poor performance on the UDF problem set shows that it is more suitable for complex problems, whereas EIB finds positive improvement across a larger range of problems. Both of these approaches outperform the E mechanism, indicating that increasing blocking over the lifecycle was beneficial.

### 4.2 Performance against the baseline

The total difference in performance between the baseline and EIB over the 2 cycles is shown in Figure 2. The difference on each two generation interval is summed with dark red denoting when the baseline performs better and light blue denoting when EIB performs better. In problems such as JY5 and JY6, both algorithms have parts of the search where they perform well, leading to no detectable difference as can be seen in the \( p \)-value in Table 2. In problems with statistically significant negative performance such as FDA1, it is not overwhelmingly negative, with a positive improvement 40% of the time. The results show strong performance overall against the baseline, indicating the strength of the epigenetic mechanism in solving dynamic problems.

### 5 DISCUSSION

The addition of an epigenetic blocking mechanism is able to significantly improve the performance of the MOEA/D-DE algorithm on a range of dynamic problems.

Both the EIB and EIP variants performed better on more problems compared to E, suggesting that varying the rates at which the mechanism triggers and the variables that are blocked is more effective than keeping the parameters static. From evolutionary theory, this behaviour is expected in a dynamic environment with epigenetic variations that are guided rather than random [12]. The varying rates give more control over the convergence and diversity of the populations. The increased consistency from EIB compared to EIP shows the effectiveness of blocking more variables, even at a slower rate. Convergence is increased with more variables blocked, hence it performs well in general and on convergence based problems like UDF. EIB blocks fewer variables but more often, finding success when the correct variables are blocked, but worse performance on the wrong variables. More diversity can be retained with EIP as only a small number of variables are blocked compared to blocking a majority of variables in EIB. The increased diversity would explain EIP’s better performance on the complex JY problems, and it would be expected for EIP to perform well on complex real world problems where diversity plays a larger role than convergence.

The epigenetic mechanism shows more sensitivity to Pareto set changes because the variables are directly blocked. Better performance is observed on Category II and III problems where there are Pareto front changes, and worse performance on the Category I problem where there are only Pareto set changes. A change in the Pareto front is analogous to a change in objective (fitness optimum) in the natural world, which epigenetic processes can more quickly adapt to. A change in the Pareto set is more complicated and can be related to the concept of plasticity [18], where the environment influences the developmental stage of phenotypes.

An important advantage of this epigenetic mechanism is the ability to include the mechanism into any crossover method of a genetic algorithm. The mechanism sits on top of the crossover
category II problems

which variables should be blocked.

world, epigenetics also sits on top of existing genetic mechanisms to allow for quick adaptation.

6 CONCLUSION

This paper demonstrates the impact of including a simple epigenetic blocking mechanism into an existing evolutionary algorithm, and the advantages epigenetics can provide to algorithms solving dynamic problems. The epigenetic mechanism improves upon the baseline MOEA/D-DE algorithm on 12 of the 16 dynamic multiobjective test problems, with a conclusively negative result on only 1 problem. Increasing the number of variables blocked helps increase convergence, giving consistent improvement on all categories of test problems. Increasing the rate of which the mechanism is activated is more effective on the complex JY problems, suggesting a retention of diversity in the population.

There are further epigenetic mechanisms and features to look into. In nature, epigenetics enable fast adaptations triggered by environmental cues, and the epigenetic method itself is inherited by future generations. The next step in the proposed blocking mechanism is to include environmental cues to direct how the mechanism should be triggered, and a form of inheritance to direct which variables should be blocked.

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