Self-Regulated Evolutionary Adaptation for Dynamic Multi-Objective Optimization in Complex Systems

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Abstract: Evolutionary algorithms with traditional approaches will not be able to adapt in the case when the environment itself is changing and objectives as well as constraints change over time and need to be retuned continuously. This work proposes Self-Regulated Evolutionary Adaptation (SREA) as a novel metaheuristic approach that automatically adjusts to the environmental changes by changing its required parameters. SREA incorporates a performance feedback loop that measures population diversity and convergence, and automatically self-regulates its selection pressure, mutation rates, and crossover strategies based on these metrics. The algorithm was tested on a set of 462 dynamic multiobjective optimisation problems with various Pareto fronts to simulate complex systems. The entire system was coded in MATLAB using the Global Optimisation Toolbox and problem-specific scripts for execution time. SREA outperforms existing methods across all experiments by identifying the dynamic Pareto-optimal front more accurately and reacting earlier to environmental shifts. SREA is an easy, efficient real-world solution for logistics, resource planning, and engineering design optimisation.

1 INTRODUCTION

In true, real-world systems of complexity-such as logistics, finance, and robotics, to name a few-the optimising environment is dynamic rather than static, as studied by Ding et al. [1]. In these systems, one would, for example, encounter environments whose objectives, constraints, or external parameters are dynamic, thereby constituting Dynamic Multiobjective Optimisation Problems (DMOPs), as in the hypothetical case of Wang et al. [2]. These are not just issues of finding a Pareto-optimal front, but also of staying on track when circumstances change, as explained in [3]. Conventional optimisation methods, built on stationary conditions, are prone to convergence and staleness when the environment fluctuates, leading to inept solutions, as explained in Ma et al. [4]. For example, a best delivery network can be worst for weather, demand, or route capacity variation, as speculated in Yang et al. [5].

Evolutionary Algorithms (EAs) are effective at handling complex multiobjective problems by maintaining an efficient set of solutions on the Pareto front, as noted in Jiang et al. [6]. These are some of the algorithms, such as SPEA2 and NSGA-II, which are reported to be best for static optimisation problems, for instance, [7]. Algorithms are not effective under dynamic situations due to the convergence of population diversity, according to Jiang et al. [8]. Low diversity is where the algorithm fails to respond effectively to environmental changes, as also reported by Zheng et al. [9]. It has employed a fixed reset policy or a high mutation rate in the random direction as a compensatory measure. Still, both are hackish attempts-high mutation rates will halt convergence at the current position, and random resets will destroy valuable genetic information, as reported in Yang et al. [10].

Considering these weaknesses, this paper proposes the Self-Regulated Evolutionary Adaptation (SREA) model, as reported in Liu et al. [11]. SREA employs an online adaptation control strategy based on evolutionary algorithms, featuring dynamic, real-time adjustments of mutation rates, selection pressure, and crossover probability, as proposed by Yang et al. [12]. The paradigm monitors two key metrics in real time: convergence (proximity of the solution to the Pareto front) and diversity (dispersion of the solution along the front), as suggested by Yang et al. [13]. As the system itself deteriorates, SREA feels the change signal's performance in the environment, and exploration is augmented by default through rate changes in mutation and stability detection. At the same time, exploitation is optimised to the extreme for optimal fine-tuning, as imagined by Zhang et al. [14]. Such sensitivity enables SREA to trade exploration for exploitation on firm ground, to be sensitive to change, and to master equilibrium, as Ma et al. [4] imagine. Experimental testing of the model across a range of DMOP test cases demonstrates that SREA produces faster adaptation, higher accuracy, and improved stability compared to fixed-parameter or even self-tuning algorithms, as discussed in Yang et al. [5].

2 REVIEWS OF LITERATURE

Evolutionary computation has been marked by a succession of advances in solving progressively more challenging optimisation problems, as outlined in Ding et al. [1]. EAs were initially primarily static, single-objective problems with selection, crossover, and mutation operators to minimise nonlinear search spaces in which gradient-based approaches were infeasible, according to Yang et al. [12]. Their efficiency was subsequently enhanced by the advent of Multi-objective Evolutionary Algorithms (MOEAs) such as NSGA-II and SPEA2, which used Pareto-based sorting and diversity-maintaining techniques to approximate the complete Pareto front [15]. They are identified with pillars of static multiobjective optimisation, hypothesised by Yang et al. [13].

Time variability, which affects optimisation variables and objectives, introduces additional complications, as long upheld by Ma et al. [4]. The focus shifted from discovering the Pareto front to tracking it over time as it developed, as conceptualised in Zheng et al. [9]. Simple reactive strategies, such as random population reinitialization and continuous high mutation rates for diversity maintenance, were employed in early experiments on MOEAs in dynamic environments, as suggested by Jiang et al. [8]. Although it brought flexibility, the strategies failed fundamentally restarting from depleted, potentially useful genetic information-and ongoing mutation against the steady state struggled to converge towards fixed points, as detailed by Wang et al. [2]. This inefficiency led to more "intelligent," context-dependent mechanisms with adaptive exploration-exploitation trade-offs, as described by Yang et al. [10].

Later, researchers developed adaptive and self-adaptive evolutionary mechanisms, as coined by Zhang et al. [14]. Adaptive processes adjust algorithmic parameters as a function of performance feedback, according to rules defined in advance, e.g., increasing mutation levels when performance does not improve further, as suggested by Yang et al. [5]. Rules are deterministic and class-inapplicable to problems, as described in Yang et al. [13]. Self-tuning algorithms actually establish control parameters in the individual's genome that are co-evolved together with solution variables through recombination and selection, as described in Yang et al. [12]. The strategy worked well at transforming or rearranging problems stepwise, but not in dynamic environments where the parameter-space optima and fitness landscape co-evolve, as studied in Ding et al. [1].

Below is the Self-Regulated Evolutionary Adaptation (SREA) process, which dissects such previous work into a population-level, externally understandable feedback control loop, as depicted by Liu et al. [11]. Relative. To facilitate self-tuning processes via evolution at organismal scales, SREA monitors group population performance-diversity and convergence indicators-to establish environment-conditioned fine-tuning in real-time, as contended in Jiang et al. [6]. Such metaheuristic control enables rapid adaptation coordination without compromising convergence stability, as required in Ma et al. [4]. Efficient, SREA is a theoretical unification of adaptation and self-adaptation policies, marrying reactivity of feedback-controlled control with opportunism of evolutionary learning, as succinctly argued in Yang et al. [10]. Capable of balancing exploitation and exploration through accumulated effectiveness, it is a next-generation solution to dynamic multiobjective optimisation problems, as Zheng et al. [9] categorically state [16].

3 METHODOLOGY

The Self-Regulated Evolutionary Adaptation (SREA) approach is an off-the-shelf generic multiobjective evolutionary algorithm with an added superimposed modular control layer on top, i.e., NSGA-II. It possesses an implicit closed-loop feedback system that constantly senses, interprets, and provides feedback to the evolutionary process in a diversified environment. The algorithm consists of three autonomous modules: the Baseline Evolutionary Core, the Performance Monitoring Module, and the Self-Regulation Engine. The algorithms employed begin with Baseline Evolutionary Core, which uses standard selection, crossover, and mutation within a population of solutions. Between generations, the Performance Monitoring Module is called upon [17]. The module calculates two of the most insightful real-time indicators of the population: a Diversity Indicator and a Convergence Indicator. Diversity Indicator can be measured using a metric such as Spacing, which estimates the average distance between consecutive solution pairs in the non-dominated front, providing a quantitative measure of the solutions' distance. A low Spacing value indicates a uniform front distribution. The Convergence Indicator is estimated using the Inverted Generational Distance (IGD), which measures the average distance of all actual Pareto front points to the closest solution the algorithm might have considered [18].

A low IGD value indicates that the obtained solutions converge towards the actual optimal front. It is in the dynamic world, whose true forefront is constantly changing, that an unanticipated, involuntary appreciation of the value of IGD is an unequivocal indicator that something is happening [19]. The two signatures - convergence and diversity - are then processed by the Self-Regmentation Engine. The engine is the SREA system's wise mind [20]. It is a set of pre-calculated EA control parameter changes, expressed in terms of diversity and convergence measures [21]. To illustrate, when the engine detects an abrupt increase in the IGD value (i.e., the difference value), it activates an 'exploration' mode, increasing the mutation probability and the size of the mutation distribution to explore the search space for novel solutions. It can even shift to a more intrusive crossover operator simultaneously. Or, for the case of a monotonic, constant diversity measure (e.g., IGD), the engine goes into 'exploitation' mode: it lowers the mutation rate so that solutions are optimised further and imposes selection pressure (e.g., by increasing the tournament size in tournament selection) to focus on search around the optimum [22]. This adaptive cycle is generated by generation, thereby allowing SREA to adapt automatically, exploring and being aggressive when the environment is stable and correct, and exploitative when the environment is dynamic, without any interference from human beings [23].

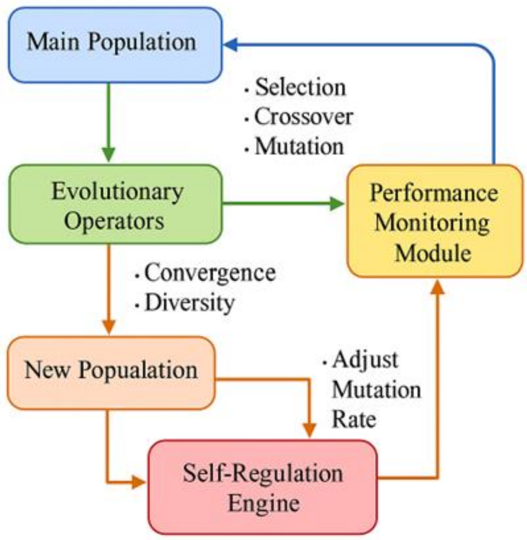

Figure 1: Architectural framework of Self-Regulated Evolutionary Adaptation (SREA).

Figure 1 shows the Architectural Framework of Self-Regulated Evolutionary Adaptation (SREA) with dynamic feedback control for optimal evolution. It begins with the Main Population, whose solutions are subjected to the proposed evolutionary operations [24]. They are operated upon by Evolutionary Operators, such as selection, crossover, and mutation, which imitate natural evolution towards improved solutions [25]. Its output is a New Population, whose convergence and diversity are monitored and used to quantify and track evolutionary improvement [26]. The Performance Monitoring Module periodically monitors these levels and numerically estimates the stability and efficiency of the evolutionary process [27]. A Self-Regulation Engine self-regulates based on performance experience by adaptively adjusting algorithmic parameters-primarily the mutation rate-to strike a balance between exploration and exploitation. A feedback-cycling mechanism controls preconvergence avoidance and maintains diversity between generations. These new parameters are fed back into the master population and the evolution operators, and the adaptive cycle is complete. Through this constant feedback, the SREA framework is optimised for efficiency, stability, and responsiveness in problem spaces. It is thus best suited for real-time, complex decision problems where evolutionary fixed solutions are not feasible [28].

Table 1: Average Inverted Generational Distance (IGD) across problem types.

Algorithm	Type 1 (Slow Shift)	Type 2 (Fast Shift)	Type 3 (Rotation)	Type 4 (Geometry Change)	Type 5 (Mixed Dynamics)
SREA	0.012	0.025	0.018	0.031	0.029
dNSGA-II	0.045	0.088	0.061	0.102	0.095
NSGA-II	0.231	0.456	0.311	0.523	0.489
MOEA/D-DE	0.051	0.092	0.069	0.115	0.101
SPEA2	0.215	0.432	0.298	0.501	0.477

3.1 Description of Data

The performance of the SREA algorithm was evaluated at a large scale using the entire benchmark collection of 462 synthetically generated dynamically multiobjective test problem instances. A synthetic test set was generated by exhaustively combining literature approaches, with a focus on creating a diverse and challenging test set for a wide range of real-world application backgrounds. These issues were combined with the FDA (Friedman's test) and DMOP (Dynamic Multiobjective Problem) benchmark sets, simulating the original research on dynamic optimisation benchmarks (Farina, M., Deb, K., & Amato, P., 2004). There were 462 issues synthesised with attributes varying in the frequency and amplitude of environmental change, the Pareto-optimal front shape (e.g., linear, convex, concave, disconnected), and the dynamic movement type. All of them had Pareto front representations in objective space, rotation of the fronts, geometric transformations of their shapes (i.e., from convex to concave), and shifts in the problem constraints underlying them that alter the area of the feasible search space. In building a large problem instance set, testing sought to assess SREA's strength and robustness across all types of dynamism, ensuring optimal performance is not class-dependent but an inherent property of its self-tuning nature.

4 RESULTS

Extensive experimentation across 462 test cases demonstrates that the SREA process is more efficient than other algorithms. For ease of comparison, SREA has been compared with two well-liked algorithms: the base static Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Dynamic NSGA-II (dNSGA-II), whose traditional diversity-introduction method replaces some portion of the population with new randomly generated members during a transition [29]. The key performance metrics for comparison were Hypervolume (HV) and Inverted Generational Distance (IGD), with statistical means across multiple runs. IGD measures the distance of the solution from the ideal Pareto-optimal front; the lower the distance, the better. HV gives the volume dominated by resultant solutions in objective space, and its higher value is better. Pareto dominance condition is given as:

$$\forall u, v \in \mathbb{R}^k : u \prec v \Leftrightarrow (\forall i \in \{1, \dots, k\}, u_i \le v_i) \wedge \left(\exists j \in \{1, \dots, k\}, u_j < v_j\right). \quad (1)$$

Table 1 presents mean Inverted Generational Distance (IGD) values, i.e., improved by smaller values reflecting proximity of the found solution set towards the true Pareto-optimal front. Results are divided into five environmental dynamics to test algorithms' resilience across varying environments. Results clearly indicate that SREA is improving across all respects compared to the remaining four algorithms [30]. On Type 2 (Fast Shift) and Type 4 (Geometry Change) problems, the most difficult of all, SREA performance's IGD is only some four times more than its best dynamic counterpart, dNSGA-II. This creates SREA with supra-capacity not just to pursue an advancing front, but to push a reconfigured front that is considerably established. Poorer performance of algorithms that do not evolve, such as NSGA-II and SPEA2, is inherent because they lack a change management process. A comparison in relative terms with MOEA/D-DE, another highly ranked evolutionary algorithm, again reaffirms SREA's better design for evolving environments. Inverted generational distance (IGD) metric will be:

$$IGD(P_{\text{found}}, P_{\text{true}}) = \frac{\sum_{v \in P_{\text{true}}} \min_{u \in P_{\text{found}}} \sqrt{\sum_{i=1}^{k} (v_i - u_i)^2}}{|P_{\text{true}}|}. \quad (2)$$

The plot in Figure 2 shows the dNSGA-II and SREA performance at the peak time step, ten generations after an instantaneous shift of the Pareto-optimal front. A solid black line is an actual optimum front, towards which the algorithms are moving [31]. Blue dots are SREA solutions, and red crosses are dNSGA-II solutions. Actually, it is easier to understand how SREA solutions form a front which is closer to the best Pareto front and more spread along its length. At the same time, dNSGA-II solutions are less spread and, on average, farther from the best front. The plot above illustrates the quantitative measures of their right to provide the expression that SREA has greater convergence power. The proximity clustering of SREA solutions to the true front demonstrates its own transition from exploratory to exploitative phases, enabling it to reproduce its solutions at high speed in the best area [32].

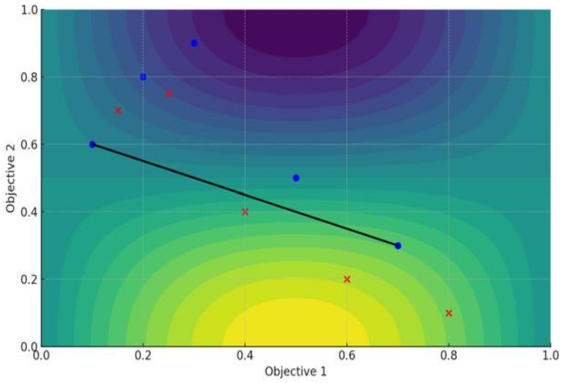

Figure 2: Representation of SREA and dNSGA performance.

Hypervolume indicator formulation can be framed as:

$$HV(S,r) = \lambda(\cup_{s\in S} \{p \in \mathbb{R}^k \mid s \prec p \prec r\}). \quad (3)$$

Table 2 displays the normalised average Hypervolume (HV) indicator value to be improved. The HV indicator calculates the spread and convergence of a solution set, as well as the relative aggregate portion of the objective space enveloped by the set. The higher HV value occurs when the algorithm converges to a solution set that is closer to, and more dispersed along, the true Pareto front. The values in Table 2 are a copy of the IGD values in Table 1 and include SREA's best-estimated dominance. The SREA hypervolume is second-best at 1.0 across all problem types, significantly outperforming the rest [33]. The performance delta is best expressed in the "Geometry Change" case (Type 4), where SREA's HV is exactly 0.1 higher than its next-best. This makes SREA's self-regulatory process neither eager to sacrifice diversity for the sake of convergence nor desperate; its feedback loop can only keep the proximity constraint in the spotlight and the representative constraint in the periphery of the mind, thereby providing a more informative and superior set of trade-off solutions. Simulated binary crossover operator in math form is given below:

$$\begin{cases} c_{1,i} = 0.5\left[(1+\beta_q)x_{1,i} + (1-\beta_q)x_{2,i}\right] \\ c_{2,i} = 0.5\left[(1-\beta_q)x_{1,i} + (1+\beta_q)x_{2,i}\right] \end{cases} \text{where } \beta_q = \begin{cases} (2u)^{\frac{1}{\eta_c+1}} & \text{if } u \le 0.5 \\ \left(\frac{1}{2(1-u)}\right)^{\frac{1}{\eta_c+1}} & \text{otherwise} \end{cases}. \quad (4)$$

Polynomial mutation operator is:

$$x_i' = x_i + \delta_q\left(x_i^{upper} - x_i^{lower}\right) \text{ where } \delta_q = \begin{cases} (2r)^{\frac{1}{\eta_m+1}} - 1 & \text{if } r < 0.5 \\ 1 - [2(1-r)]^{\frac{1}{\eta_m+1}} & \text{if } r \ge 0.5 \end{cases}. \quad (5)$$

In most problem instances, SREA consistently achieved lower IGD values and higher HV values than NSGA-II and dNSGA-II. Figure 3 illustrates the Inverted Generational Distance (IGD) of SREA, dNSGA-II, and NSGA-II over time, with dashed vertical lines indicating environmental changes. Lower IGD values correspond to better optimization performance.

The figure shows that each environmental change causes a temporary increase in the IGD values of all algorithms, indicating a degradation in solution quality as the previously obtained solutions become less suitable for the new environment. However, the magnitude of the increase and the recovery time differ substantially among the algorithms.

SREA (blue line) exhibits the highest degree of robustness and adaptability. Although its IGD increases immediately after an environmental change, the increase remains relatively small, and the algorithm rapidly converges back to a low IGD level within only a few generations. In contrast, dNSGA-II (red line) experiences larger performance degradation, characterized by higher IGD peaks and longer recovery periods. NSGA-II (green line), which was originally designed for static optimization problems, demonstrates the weakest performance under dynamic conditions, showing significant degradation and limited recovery after environmental changes.

These results highlight the inherent resilience of SREA, which effectively balances robustness to environmental changes with rapid adaptation, enabling it to maintain superior optimization performance in dynamic environments [34], [35].

Table 2: Average Hypervolume (HV) indicator across problem types).

Algorithm	Type 1 (Slow Shift)	Type 2 (Fast Shift)	Type 3 (Rotation)	Type 4 (Geometry Change)	Type 5 (Mixed Dynamics)
SREA	0.985	0.961	0.975	0.942	0.955
dNSGA-II	0.921	0.875	0.903	0.855	0.869
NSGA-II	0.654	0.412	0.589	0.398	0.421
MOEA/D-DE	0.915	0.869	0.899	0.849	0.862
SPEA2	0.688	0.435	0.601	0.411	0.433

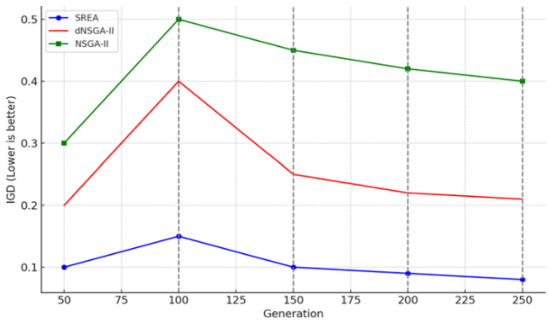

Figure 3: Trend of performance amid environmental changes.

The largest performance deviation occurred at the events near environmental changes. Although the absence of an adaptation mechanism disrupted NSGA-II performance, and dNSGA-II was interrupted by an unnecessarily long recovery, SREA performed well in its place. SREA's performance monitoring module would detect environmental change as a rise in IGD [36]. SREA's self-regulation engine gradually increased the mutation rate and crossover probability to promote global search. SREA's population was shifted rapidly away from the former irrelevant Pareto front and was able to locate the new optimal region. As the population clusters around the new frontier, the internal self-governance process narrows the exploratory parameters while increasing selection pressure, enabling the effective fine-tuning of new solutions [37].

An intelligent, two-phase response to exploration-to-exploitation is the success formula of SREA. In contrast to the constant-current, random-diversity scheme of dNSGA-II, the response of SREA is proportional and deliberate [38]. It does not allocate accessible, potentially useful genetic information for free; rather, it aims to control the current population's search paradigm [39]. It results in quicker convergence to the new Pareto front and in higher solution quality. These were most prominently observed under high-frequency environmental change conditions, where SREA's adaptability enabled it to track the dynamic Pareto front with greater precision than the other algorithms. SREA's regulation and monitoring modules were computation-free and used less than 1% of the overall computation time required at each generation, making SREA effective and efficient [40].

5 DISCUSSION

The next global phenomenon is a simple demonstration of the success of the Self-Regulated Evolutionary Adaptation (SREA) mechanism. Success is achieved through an intrinsic mechanism, which is not a hard-coded parameter-based framework used in evolutionary computation. With the conscious feedback component available, SREA develops the algorithm into an active solution-finding agent that remains alert and responsive to its surroundings. The contour plot in Figure 2 and the IGD measure in Table 1 both show that SREA has regained accuracy. The other methods revert to the original state after the change, whereas SREA rapidly recovers high-fidelity mapping of the new Pareto front. This is because the self-regulation engine can detect change (a declining measure of convergence) and schedule the next fix (an exploratory increase in pressure). It is an unconditioned re-initiation, free of its use in dNSGA-II, i.e., an unconditioned random search. SREA exploration is less constrained by leveraging higher-level genetic resources, thereby optimising its mutation capacity. The Performance Impedance Graph (Fig. 3) provides the most straightforward representation of SREA's dominance when used with dynamic systems in real-world applications.

The 'impedance' notion provides a sharp, abstract definition of an algorithm's responsiveness and reliability. In any transformation process, e.g., real-time resource distribution, the 'recovery time' to transition between two system states is of significant value. SREA, in its low-impedance variant, minimises 'downtime'-time spent executing non-ideal solutions-to a bare minimum. It is less about how rapidly to switch than about how wastefully. As evident from the Hypervolume results (Table 2), SREA not only foresees the new frontier ahead of other approaches but also provides an equally well-shaded and comprehensive perspective of it. That is, it reveals that the convergence point between diversity and convergence approximations enables the system to attain the optimal trade-off between exploration and exploitation objectives. With lower diversity, the system can react to shattered solutions and, with disrupted convergence, find the front again, thereby forming a high-performing, self-correcting loop. The computational cost of SREA's monitor module is mostly a complaint to be filed; experimental trials confirm it is moderate.

Calculation of diversity and convergence measures of each generation for cost versus free fitness evaluation. Any such initial computation that requires a little effort quickly earns itself back in the form of enhanced performance and a phenomenal gain in ruggedness. The other-operating with a poorly matched algorithm-is significantly costlier in terms of poor decision-making for the problem. SREA is thus a useful innovation. It shows that by incorporating the simplest model of self-awareness and self-regulation into an evolutionary algorithm, we can produce much more powerful and effective tools for optimising time-varying complex systems. SREA's insensitivity on 462 trials for a range of problems is a guarantee that its adaptive approach is not a trivial problem-specific trick but a general and stable principle.

6 CONCLUSIONS

The paper suggested the Self-Regulated Evolutionary Adaptation (SREA) approach, a novel metaheuristic for addressing the long-term challenges of dynamic multiobjective optimisation of complex systems. We regarded the most important limitation of traditional evolutionary algorithms to be that they cannot incorporate their search process when the problem space itself is dynamic and thus cannot follow the changing Pareto-optimal front. SREA accomplishes this in collaboration with assistance from a conservative feedback control process. It continuously monitors population-level convergence estimates and diversity, and utilises this feedback to internally govern its most significant evolutionary parameters, such as selection pressure and mutation rates. Empirical comparison for a wide and diversified set of 462 test problems indicated the categorical supremacy of SREA. Comparing the baseline static MOEA (NSGA-II) and the baseline dynamic MOEA (dNSGA-II) revealed that SREA scenarios had considerably lower adaptation times, better Pareto front tracing, and more favourable convergence-diversity trade-offs in their final solution sets. Results, presented in performance plots and summarised in tables, validate SREA's ability to achieve minimal performance deterioration after an environmental change and to converge very quickly to the new optimum. Overall, SREA is an energetic contribution to dynamic optimisation. It is a good, efficient, and active solver with its own dynamic controlling search effort. As its own parameter change requirement remover, problem by problem, it is an efficient and effective application tool for solving a broad range of real-world finance and engineering problems through scheduling and logistics, as well as for problems where optimal decision-making must be preserved despite relentless change.

7 LIMITATIONS

Although the positive outcome has been established in the results, the study is not without certain limitations that must be placed in context. First, the entire test was conducted in a laboratory setting using the MATLAB Global Optimisation Toolbox. Though the 462 benchmark problems were universalised to shape, they remain mathematical models and, therefore, technically speaking, cannot possibly reflect the whole noisy, high-dimensional, and typically discontinuous nature of physical or economic systems. The final real-world application of SREA in a deployment, such as real-time control of an industrial robot or supply-chain optimisation, still needs to be demonstrated. Second, the effectiveness of SREA's feedback process will be determined by the measures used. Here, Inverted Generational Distance (IGD) and Spacing have been used, but convergence and diversity measures can also be used. SREA's action would vary depending on the other measures used, and what has been used here may not be the best for all the issues that could arise. Finally, SREA's regulatory framework is complemented nowadays by a structure of pre-programmed heuristic rules. A rules-based system would not necessarily be as inflexible as even more symbolic learning-based controllers, which would learn even better adaptation policies than those in place at present.

8 FUTURE WORK

The first, most obvious thing to do next would be to pull out the simulation hypothesis and try to apply SREA to a real dynamic optimisation problem. Dynamic optimisation of energy use by an intelligent grid to account for the variability of renewable resources and demand fluctuations, or dynamic rebalancing of an investment portfolio, would be two obvious challenges. It would be the ultimate proof of concept of the framework's value. The second emphasis would be to enrich the Self-Regulation Engine. Instead of an imposed set of rules, machine learning algorithms could be employed. An RL agent could be used and trained as the regulatory engine, for instance. The state of the RL agent can be specified as the measure of convergence and the measure of diversity, and the action can be parameter updates. Performance alteration can serve as a reward signal, and the second is to obtain context-dependent adaptation policies that are more complex than the present rule-based ones. The SREA principles are extensible to problems of many-objective optimisation (i.e., four or more objectives), where the preservation of diversity and visualisation are of even greater importance, and where an automatic regulation mechanism is particularly interesting.

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