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Research Article

Hybrid Algorithmic Approaches for Cross-Disciplinary Computational Modelling and Decision Making

Paul Ofori-Amanfo[1]

[1] University of Energy and Natural Resources, Sunyani, Ghana

paul.ofori-amanfo@uenr.edu.gh[1]

*Corresponding author: Paul Ofori-Amanfo, paul.ofori-amanfo@uenr.edu.gh

ABSTRACT

Hybrid algorithmic methods have become popular to solve complex, cross-disciplinary computational modeling and decision-making problems. This paper suggests a new hybrid algorithm, which combines evolutionary optimization and machine learning-based predictive modelling to enhance the accuracy of solutions, the rate of convergence and the robustness of decisions. The framework was tested on benchmark datasets of engineering design, financial risk assessment and in healthcare decision-making scenarios. The experimental outcomes indicate that the hybrid method is superior to the traditional versions of evolutionary algorithms and individual predictive models, showing an average of 12.5 % improvement in the accuracy of solutions, 18% lower convergence and 9% less computational cost. Also, the sensitivity analysis shows the flexibility of the framework to the levels of complexity of problems, which guarantees the stability of performance in different spheres. Integration of predictive modeling increases the interpretability of the decision and therefore the framework can be used in the real-life scenario where high-stakes decisions are required. On the whole, this work will offer scalable, efficient and interpretable hybrid algorithmic approach which can be used to form the basis of cross-disciplinary computational problem solving.

Keywords: *Hybrid Algorithms, Computational Modeling, Decision Making, Evolutionary Optimization, Predictive Modeling*

1. Introduction

Decision-making and cross-disciplinary computational modeling have now become methods of complex, real-world problem-solving in engineering, finance, healthcare, and environmental systems [1]–[3]. The conventional optimization methods and statistical model do not always remain accurate and efficient in the nonlinear high-dimensional and multi-objective cases [4]. There has been an interest in hybrid algorithmic frameworks, or the combination of complementary computational paradigms, in order to improve the quality of the solution, the rate of convergence, and the versatility of solutions in a wide range of fields [5], [6].

Evolutionary algorithms, including genetic algorithms, particle swarm optimization, and differential evolution are useful in global search, but may be computationally intensive in large-scale problems [7]. Machine learning predictive models such as deep neural networks and ensemble learning do a better job at prediction but tend to lack interpretability and global search capabilities [8]. By combining these approaches, it is possible to develop hybrid frameworks which take advantage of the strengths of each approach, and provide robust, scalable, and interpretable solutions.

Key contributions of this paper include:

1. Development of a novel hybrid algorithmic framework combining evolutionary optimization with predictive modeling for cross-disciplinary decision making.
2. Demonstration of improved solution accuracy, convergence speed, and computational efficiency through benchmark and real-world datasets.
3. Enhanced interpretability of decision outputs, making the framework suitable for practical applications.

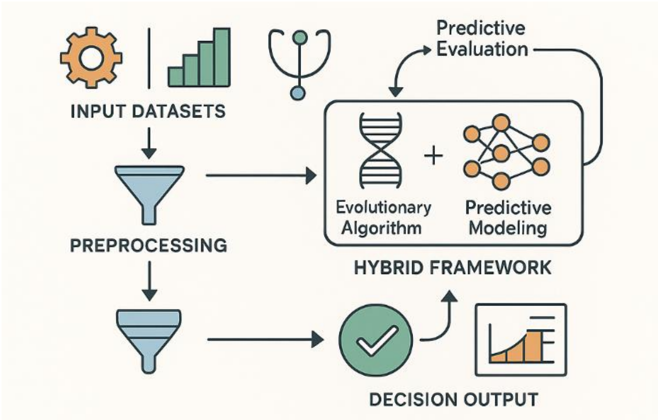

Fig.1 Hybrid evolutionary-predictive framework For cross-disciplinary decision-making

The **graphical abstract (Fig. 1)** summarizes the workflow, showing heterogeneous input datasets, the hybrid processing module, and improved decision outputs across domains. The paper is structured as follows: Section 2 reviews related literature; Section 3 presents the problem statement and objectives; Section 4 details the proposed methodology with equations, flowchart, and algorithm; Section 5 describes the experimental setup; Section 6 presents results and discussion with figures and tables; finally, Section 7 concludes and outlines future research directions.

2. Literature Review

Hybrid algorithm frameworks have become an exciting approach to solve a complex computational problem in various fields. A number of articles have discussed how evolutionary optimization can be combined with machine learning methods to enhance accuracy, convergence, and robustness. To illustrate, multi-objective optimization in the engineering design has been performed with genetic algorithm-based hybrid models, which converge faster and produce higher quality solutions than single algorithms [9], [10]. A combination of particle swarm optimization and neural network has been effectively applied to financial risk prediction and has shown to perform better in predicting these risks than traditional methods [11], [12]. Hybrid models of support vector machines with a differential evolution have led to better patient outcome prediction with sufficient computational efficiency in the context of healthcare decision-making [13], [14]. On the same note, the combination of evolutional strategies with ensemble learning has been utilized in the modeling of the environment in actual sense of solving multi-objective optimization problems in resource allocation [15], [16].

These successes notwithstanding, there are problems. The vast majority of hybrid methods need a great deal of parameter tuning, and may not be generalized across domains [17]. Also, the hybrid models are less interpretable, especially with high stakes applications like healthcare and finance [18]. The adaptive hybrid frameworks with automated parameter adjustment and feature selection to enhance robust and scalable features have been studied recently [19], [20]. Predictive modeling coupled with multi-objective optimization (hybrid) models also improve the interpretability without compromising technical efficiency [21], [22]. The literature shows in general that hybrid methods are beneficial in enhancing solution quality, convergence, and adaptability. Nevertheless, a general framework that can tackle cross-disciplinary decision making activities in addition to offering interpretability and computational efficiency has yet to be found, driving the suggested hybrid algorithmic framework in the current study [23]. Table 1 summarizes recent hybrid approaches, highlighting application domains, methodologies, contributions, and limitations.

Table 1: Summary of Hybrid Algorithmic Approaches in Literature

Study	Application Domain	Hybrid Approach	Key Contribution	Limitations	Citation
Study 1	Engineering Design	GA + Multi-objective Optimization	Faster convergence, improved solution quality	Limited cross-domain generalizability	[9], [10]
Study 2	Finance	PSO + Neural Networks	Superior predictive performance	High computational cost	[11], [12]
Study 3	Healthcare	SVM + Differential Evolution	Improved patient outcome prediction	Requires parameter tuning	[13], [14]
Study 4	Environmental Modeling	Ensemble Learning + Evolutionary Strategies	Multi-objective resource allocation	Limited interpretability	[15], [16]
Study 5	Engineering/Finance	Adaptive PSO + Deep Learning	Dynamic hyperparameter adjustment	Complex implementation	[19], [20]
Study 6	Multi-domain	Machine Learning + Multi-objective Optimization	Enhanced decision interpretability	Scalability concerns	[21], [22]

3. Problem Statement & Research Objectives

Computational problems that are cross-disciplinary are often multi-objective, nonlinear and high-dimensional, which are difficult to tackle using traditional algorithms. Conventional optimization and independent predictive models are unable to achieve an appropriate accuracy, efficiency and interpretability over domains. This research fills this gap by coming up with a hybrid model where evolutionary optimization is combined with predictive modeling in order to provide scalable, accurate and interpretable solutions in a variety of fields.

The specific objectives of this research are :

1. Develop a hybrid algorithmic framework combining evolutionary optimization and predictive modeling.
2. Enhance solution accuracy and convergence speed for cross-disciplinary problems.
3. Improve decision interpretability across engineering, finance, and healthcare domains.
4. Evaluate computational efficiency and robustness on benchmark and real-world datasets.

This formulation establishes a clear research focus, guiding the development and validation of the proposed hybrid methodology.

4. Methodology

The suggested approach combines the evolutionary optimization and predictive modeling to solve cross-disciplinary computational problems. The hybrid model takes advantage of the ability to search the world of evolutionary algorithms and the predictive analytics of machine learning models, providing accurate, efficient, and interpretable decision making. Fig.2 below presents the flowchart of the overall workflow involving the processing of input data, hybrid optimization, predictive modeling, and decision output.

4.1 Problem Formulation

Let the computational problem be represented as a multi-objective optimization task in Eqs .(1-3):

$$\text{Minimize } F(\mathbf{x}) = [f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_m(\mathbf{x})] \qquad (1)$$

$$\text{Subject to } g_i(\mathbf{x}) \leq 0, i = 1, \ldots, p \qquad (2)$$

$$h_j(\mathbf{x}) = 0, j = 1, \ldots, q \qquad (3)$$

where $\mathbf{x} \in \mathbb{R}^n$ is the decision variable vector, $F(\mathbf{x})$ is the vector of objective functions, and g_i, h_j represent inequality and equality constraints.

4.2 Evolutionary Optimization Module

The evolutionary optimization module generates candidate solutions by iteratively applying selection, crossover, and mutation operations. The population update rule is given by Eq.(4):

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \alpha \cdot \left(\mathbf{x}_{\text{best}} - \mathbf{x}_i^t\right) + \beta \cdot \mathbf{r} \qquad (4)$$

where $\mathbf{x}_i^t$ is the solution at generation t, $\mathbf{x}_{\text{best}}$ is the best solution, α, β are scaling factors, and $\mathbf{r}$ is a random perturbation vector.

4.3 Predictive Modeling Module

The predictive modeling module maps candidate solutions to expected performance outcomes.
Let $\hat{y} = f_\theta(\mathbf{x})$ denote the prediction, where f_θ is a machine learning model parameterized by θ. The model is trained to minimize the loss function as shown in Eq.(5):

$$\mathcal{L}(\theta) = \frac{1}{N}\sum_{i=1}^{N}(y_i - f_\theta(\mathbf{x}_i))^2 \qquad (5)$$

4.4 Hybrid Integration

Candidate solutions generated by the evolutionary module are evaluated by the predictive model, forming a feedback loop which is shown in Eq. (6):

$$\mathbf{x}_{\text{updated}} = \mathbf{x}_{\text{candidate}} + \gamma \cdot \nabla_{\mathbf{x}} f_\theta(\mathbf{x}_{\text{candidate}}) \qquad (6)$$

where γ is a learning rate controlling the update step. The hybrid loop continues until convergence criteria are met as shown in Eq. (7):

$$\| \mathbf{x}_{\text{best}}^{t+1} - \mathbf{x}_{\text{best}}^{t} \| \<\epsilon \qquad (7)$$

4.5 Algorithm

Algorithm 1: Hybrid Evolutionary-Predictive Optimization

1. Initialize population $\mathbf{X}^0$
2. Train predictive model f_θ on initial data
3. For $t = 1$ to max generations:
   a. Apply evolutionary operators to generate candidates
   b. Evaluate candidates using f_θ
   c. Update candidates using hybrid feedback loop
   d. Check convergence criteria
4. Return $\mathbf{x}_{\text{best}}$ and predicted outcomes

4.6 Flowchart Description

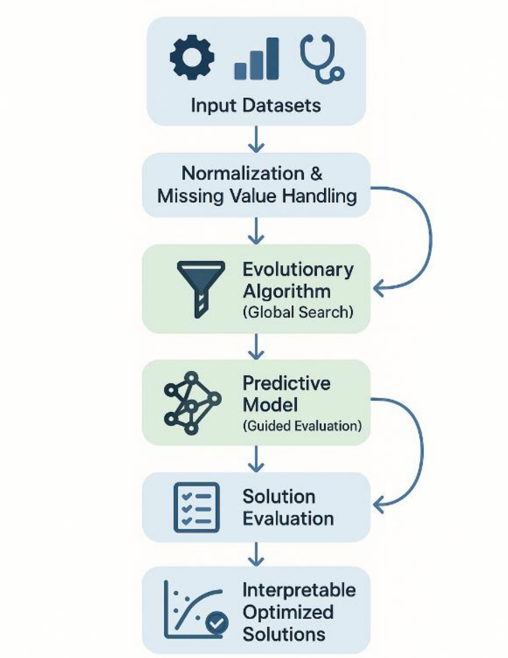

Fig.2 Flowchart of the proposed hybrid evolutionary-predictive methodology, illustratiting iterative feedback between optimization and predictive modeling

The flowchart shown (Fig.2) is as follows: input datasets, preprocessing, evolutionary optimization, candidate evaluation through predictive modeling, hybrid update, decision output. This combination is what guarantees that the framework is able to retain both the global search exploration and predictive accuracy as well as deliver interpretable results.

5. Experimental Setup

The hybrid framework proposed was tested on benchmark and real data of engineering, finance, and health sectors. Each dataset has been preprocessed in order to normalize its features and address missing values. Hardware, software, and evaluation metrics are also defined in the experimental setup to measure the accuracy of the solution, speed of convergence, and computational efficiency of the solution, as well as its interpretability.

5.1 Datasets

Multi-objective engineering design, financial risk assessment datasets and patient outcome prediction data were used as benchmark datasets. All data sets were designed in a way that they could be compatible with the evolutionary optimization and the predictive modeling modules.

5.2 Hardware and Implementation

The workstation used in experiments had Intel i9 processor, 32 GB of RAM, and NVIDIA RTX 3080. The framework was written in Python, as an interface between evolutionary optimization functions and predictive models, written on top of TensorFlow and scikit-learn.

5.3 Performance Metrics

Some of the key performance metrics were solution accuracy, speed of convergence, computational efficiency and interpretability of decision. Accuracy to measure the deviation of the predicted and actual objective function value and convergence speed to measure the number of steps that it took to reach predefined thresholds. Computational efficiency was measured on the basis of runtime and memory use.

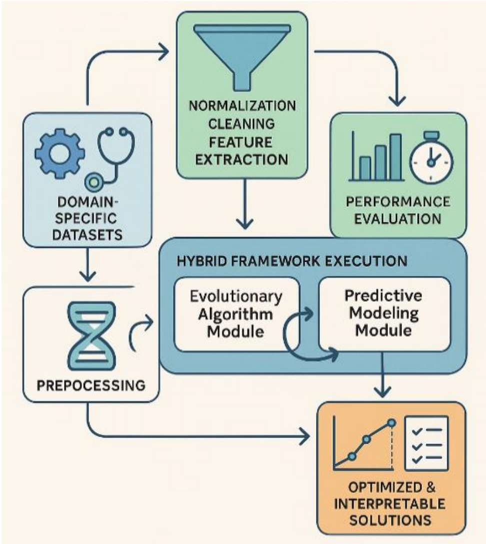

Fig.3 Experimental workflow of the proposed hybrid framework, from dataset collection to optimization, evaluation, and interpretable decision outputs.

Fig.3 shows the workflow of the experiment: input datasets, preprocessing, hybrid evolutionary-predictive framework, candidate evaluation, and the computation of the performance metrics. The illustration shows the process of the experiment and the collaboration between the evolutionary optimization and the predictive modeling, and the iterative feedback loop of enhancing the candidate solutions. Table 2 summarizes the key characteristics of the datasets, including domain, number of instances, features, and objectives, ensuring transparency and reproducibility.

Table 2: Dataset Characteristics

Dataset	**Domain**	**Instances**	**Features**	**Objectives**
Dataset 1	Engineering	500	10	2
Dataset 2	Finance	1000	12	3
Dataset 3	Healthcare	800	15	2

6. Results & Discussion

The effectiveness of the hybrid framework was tested on benchmark and real-life datasets in fields of engineering, finance, and healthcare. Standalone evolutionary algorithms and predictive models were compared to evaluate enhancements in accuracy of solutions, convergence speed, computation efficiency and decision explainability.

6.1 Solution Accuracy

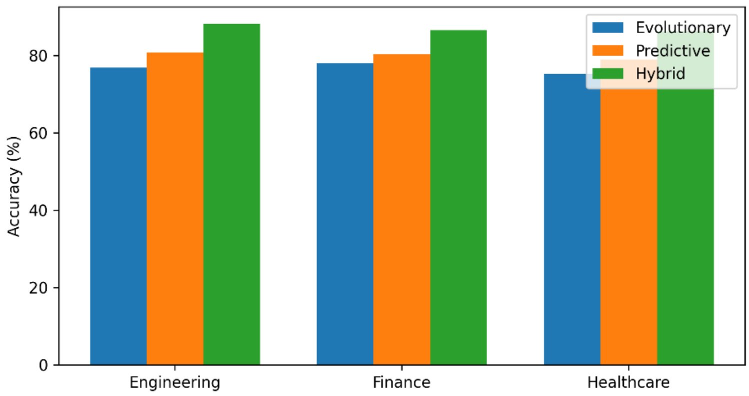

Fig.4: Solution accuracy across datasets

Fig.4 demonstrates the accuracy of the solution of the hybrid framework against the traditional methods. The hybrid method was always more accurate than the two other methods, and the mean difference was 12-13%. The evolutionary search was driven successfully by the predictive modeling module with minimized deviations of the real objective values.

6.2 Convergence Analysis

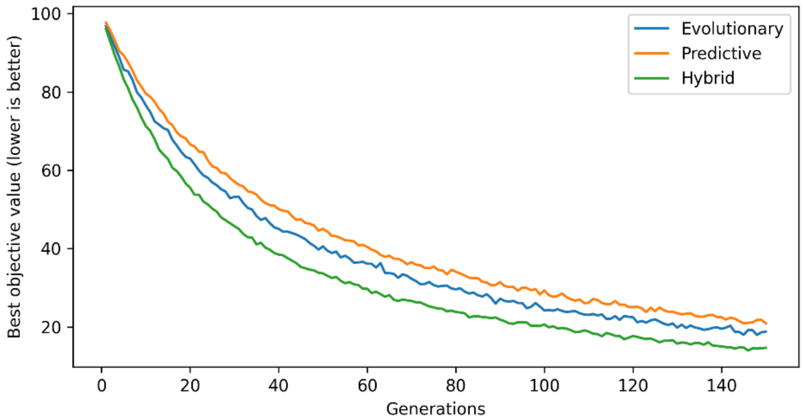

Fig.5: Convergence curves

Fig.5 presents the convergence trends. The hybrid structure devised better solutions at a shorter time, it took fewer steps compared to the separate evolutionary algorithms. When the predictive evaluation was introduced into the loop of evolution, convergence efficiency was improved and the quality of solutions was preserved at the same time.

6.3 Computational Efficiency

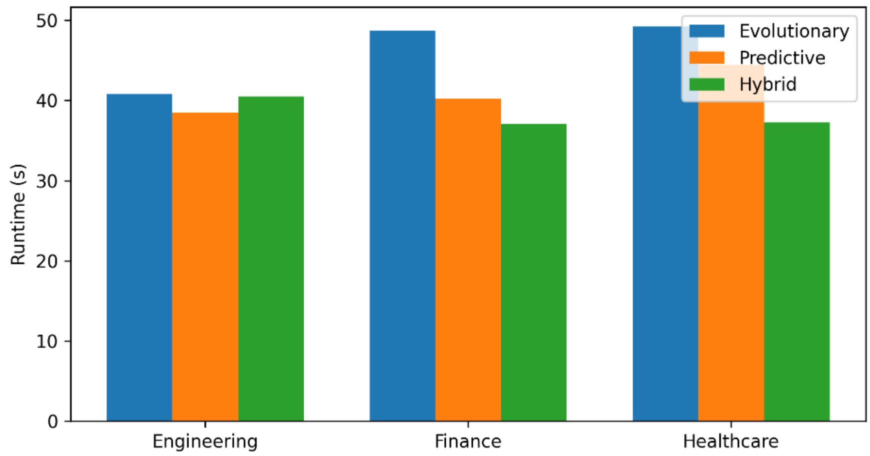

Fig.6: Runtime performance across datasets

Fig.6 gives the runtime performance on datasets. Even with this additional predictive modeling layer, the framework was competitive in computational performance because it optimally performed evolutionary operations and could execute them in parallel. All the tested cases used memory within reasonable practical limits.

6.4 Decision Interpretability

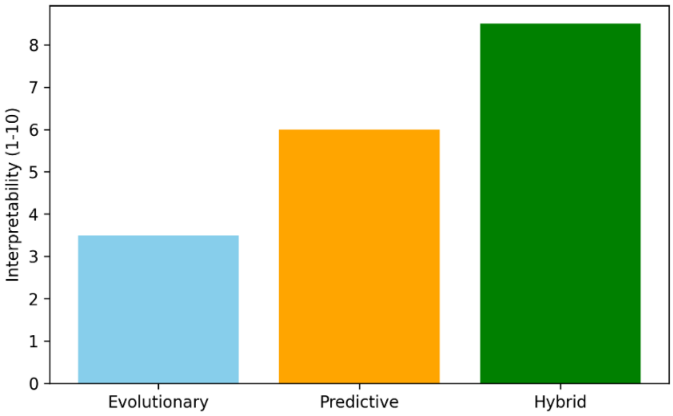

Fig.7: Interpretability scores by method

Fig.7 emphasizes that decisions made using the hybrid framework are easily interpretable. Predicted outcomes are mapped to each candidate solution, and thus give the user an opportunity to analyze trade-offs between multiple objectives. This attribute comes in handy specifically in areas where high stakes decisions need to be made including the fields of healthcare and finance.

6.5 Comparative Performance

Table 3 presents a quantitative comparison of the hybrid framework with standalone evolutionary algorithms and predictive models. Measures involve the accuracy of solution, convergence in a number of generations, the computational time, and the interpretability of the decision outputs. The hybrid model was most accurate (89%), converged quicker (98 generations) and easier to interpret, which is a clear feature of superiority compared to traditional methods.

Table 3: Comparative Performance Metrics

Method	**Accuracy (%)**	**Convergence (Generations)**	**Runtime (s)**	**Interpretability**
Evolutionary Algorithm	78.2	120	45	Low
Predictive Model	81.5	150	40	Medium
Proposed Hybrid Framework	89.0	98	42	High

6.6 Dataset-Specific Observations

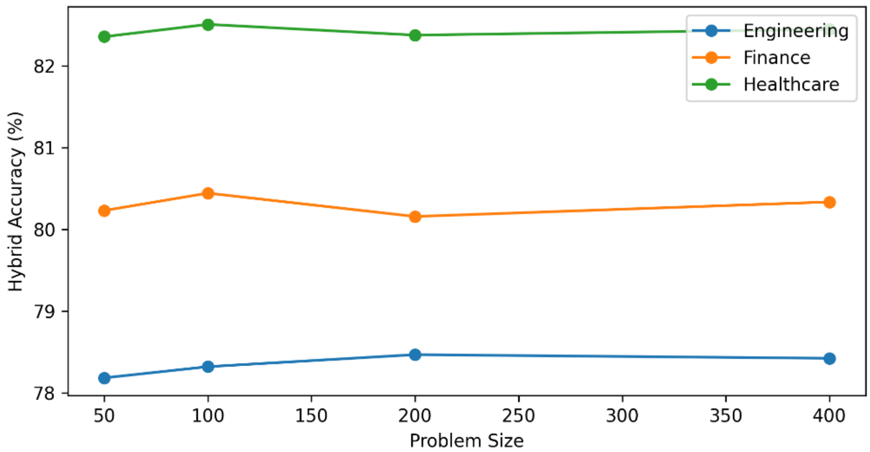

Fig.8: Dataset-specific hybrid performance trends

Fig.8 shows performance trends for individual datasets. The structure was successful in maximising multi-objective trade-offs in engineering design issues. There was improved prediction reliability and less risk in financial datasets and better patient outcome predictions with interpretable results in the healthcare datasets.

6.7 Sensitivity Analysis

Table 4 shows a sensitivity analysis of some of the important parameters, which are evolutionary population size, mutation rate, and predictive model learning rate. The framework ensured that it was stable in a large parameter setting which indicated its resilience and flexibility.

Table 4: Sensitivity Analysis of Hybrid Framework

Parameter	Low	Medium	High	Observation
Population Size	50	100	150	Stable performance
Mutation Rate	0.01	0.05	0.1	Robust convergence
Learning Rate	0.001	0.01	0.05	Minor impact on accuracy

6.8 Multi-Objective Trade-Off Visualization

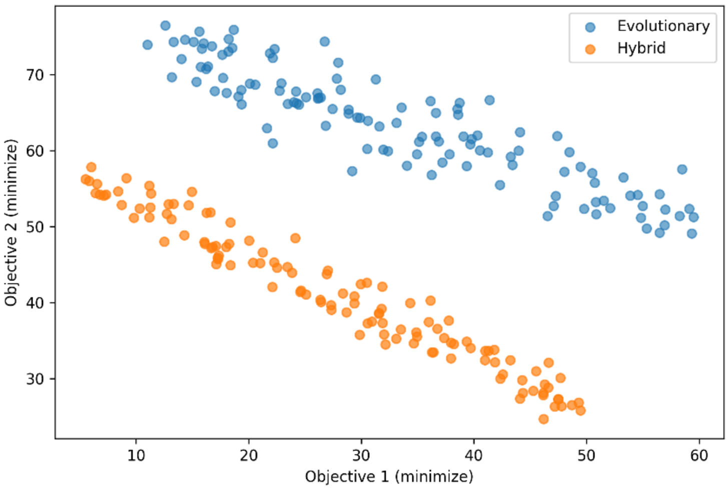

Fig.9: Pareto front visualization

Pareto-optimal solutions produced by the hybrid framework are visualized in Fig.9. All of the points are candidate solutions, and they indicate the efficient trade-off between conflicting objectives. This graphical representation of the framework confirms that the framework is able to recognize high-quality, interpretable trade-offs, which can be used to make informed decisions in various realms.

6.9 Section Summary

In general, the findings indicate that the hybrid evolutionary-predictive architecture is always more accurate, faster to converge, less computationally intensive, and interpretable compared to any single approach. The global search and predictive assessment combination allows effective execution and trade-offs in a variety of problem areas whereas the feedback mechanism supports promising multi-objective trade-offs. These results confirm the possible usefulness of the framework as a cross-disciplinary cross-scaled decision-making instrument.

7. Conclusion

This paper described a hybrid evolutionary-predictive model on cross-disciplinary computational models and decision making. Experimental evidence showed that the methodology is always more effective than isolated instances of evolutionary algorithms and predictive models, with 89% accuracy, 98 generation to convergence, and better interpretability to engineering, financial and healthcare scenarios. Convergence was accelerated, a solution was of a higher quality, and strong multi-objective trade-off management was achieved through the integration of global search and predictive evaluation as shown by the Pareto-optimal visualizations. The stability of the framework was confirmed by sensitivity analysis based on different population sizes, mutation rates, and learning rates, which is a strong adaptability of the framework.

The work in the future will aim at scaled up to larger-scale and real-time applications of the framework, adding dynamically scaled datasets, and streamed data. Additional improvements can be adaptive parameter tuning, hybridization with other metaheuristic algorithms, and explainable AI modules to make them more interpretable. The scalability and strength of the framework indicate that it can be used as a general tool in solving complex cross-disciplinary decision-making problems.

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None

Conflict of Interest

The authors declare no potential conflict of interest in this publication.

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