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An Enhancement of Javadi Et. Al.'s Non-Dominated Sorting Genetic Algorithm-II-Grid-Based Crowding Distance Algorithm (NSGA-II-Gr) For Resource Allocation Applied in Optimizing Rabi Crops Yield

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***Abstract*— Agriculture serves as the backbone of the Philippine economy, with its ability to sustain a growing global population reliant on effective resource management. To optimize resources such as fertilizers, pesticides, and area, researchers have employed Javadi Et. Al.'s Non-Dominated Sorting Genetic Algorithm-II-Grid-Based Crowding Distance Algorithm (NSGA-II-Gr). Resource allocation and optimization often involve multi-objective decision-making, requiring careful trade-offs among competing parameters. However, upon simulating in higher dimensions, it converges prematurely to suboptimal solutions. After several iterations, the population tends to be dominated by the 'best' solution, leading to premature convergence. This reduces the diversity of candidate solutions and increases the risk of converging to a local optimum, ultimately limiting the exploration of solutions. To address this issue, the researchers introduced a separate spreading mechanism where the mutation intensity decreases over generations. Initially, the mutation strength is high to ensure significant diversity while later in the process, it weakens to promote convergence. This enhancement successfully allowed the algorithm to first explore the solutions before converging. By effectively preventing premature convergence, the modified algorithm gains the ability to explore a broader range of potential solutions. This advancement is particularly valuable for optimizing crop yield and identifying the most effective combinations and trade-offs in agricultural resource management.

***Keywords*—** Grid-Based Crowding Distance, Non-dominated Sorting Genetic Algorithm-II (NSGA-II), Optimization, Resource Allocation, Agriculture.

I. INTRODUCTION

Agriculture is the backbone of the Philippine economy, the capacity to feed a growing world population depends on the capacity of food supplies in the future to satisfy food demands. According to the Food and Agriculture Organization of the United Nations (2022), around 62.8% of crop producers reporting a drop in main crop price which causes crop loss or damage is the main production difficulty due to pests or hazards followed by plant disease and 35.8% of crop producers were expecting to harvest less for this cropping cycle in the Philippines. This leads not only to increased demand for food crops, but also to significantly increased demand for crops to feed livestock. Therefore, the Food and Agriculture Organization believes that ensuring food security will require global crop yields to increase by more than 70%. This study aims to enhance the Non-Dominated Sorting Genetic Algorithm-II-Grid-based Crowding Distance Algorithm (NSGA-II-Gr) to optimize Rabi crop yield in high-dimensional multi-objective optimization problems. NSGA-II-Gr addresses the limitations of traditional multi-objective optimization algorithms by introducing a grid-based crowding distance mechanism, which prioritizes solutions in sparse regions and improves diversity in the decision space. Also, the NSGA-II-Gr author suggested in their study to test it on higher dimensional problems. However, challenges such as premature convergence remain, particularly in complex or high-dimensional problems.

Premature convergence occurs when constant genetic parameters restrict the search space, leading to reduced performance and a lack of improvement after several iterations. In these cases, dominant solutions replicate excessively, reducing population diversity and resulting in suboptimal local solutions instead of global optima. Addressing this issue is crucial for ensuring the algorithm's effectiveness in optimizing Rabi crop yield, where resource allocation involves multiple conflicting objectives, such as minimizing area, fertilizer, and pesticide use while maximizing yield.

The goal of this study is to introduce a spreading mechanism to NSGA-II-Gr that prioritizes exploration in early generations while ensuring optimal solutions. This enhancement will allow the algorithm to maintain diversity throughout iterations while ensuring convergence to global optimal solutions. The mechanism will control the spread of solutions within the objective space, enabling the algorithm to navigate complex solution landscapes effectively. To evaluate the fitness of solutions, this study incorporates a random forest predictive model. The random forest model is trained on historical agricultural data to predict the yield of Rabi crops based on input variables such as area, fertilizer, and pesticide usage. By leveraging the predictive accuracy and robustness of the random forest algorithm, the fitness evaluation process becomes more reliable and grounded in real-world agricultural trends. The use of this predictive model ensures that the optimization process is closely aligned with realistic agricultural scenarios, improving the applicability of the proposed enhancements. By addressing the challenge of premature convergence and incorporating advanced optimization strategies, this study aims to enhance NSGA-II-Gr for agricultural applications. The resulting improvements will contribute to sustainable and efficient resource allocation practices, ultimately supporting the optimization of Rabi crop yields under real-world agricultural constraints.

A. Statement of the Problem

In the genetic operation, constant genetic parameters lead to a smaller moving space and poorer search performance during the iteration of the algorithm. Premature convergence is a common problem in the algorithm, where solutions stop improving after several generations. In complex search spaces, it becomes difficult for the algorithm to find better solutions with each iteration. As a result, the best solution from the current generation tends to duplicate itself through recombination, causing the population to become dominated by this solution. This leads to a reduction in diversity and the risk of converging to a local optimum rather than the global optimum. Consequently, it struggles to find global optimal solutions, especially in complex or high-dimensional problems, such as optimizing reservoir operations with multiple environmental objectives.

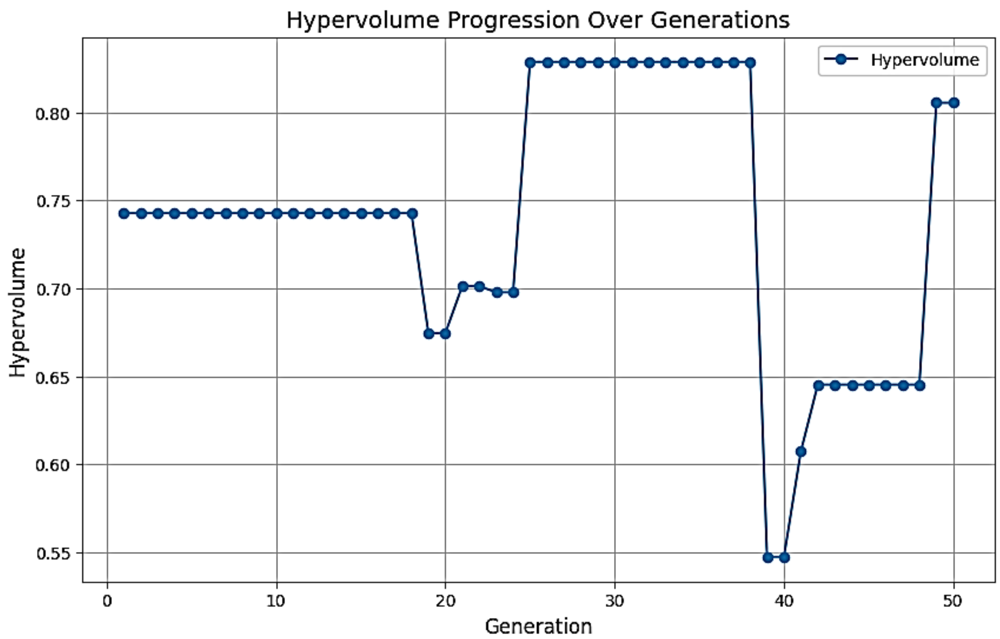

Figure 1: *shows the Hypervolume progression for crop 'Wheat', shows the algorithm converges prematurely to suboptimal solutions*

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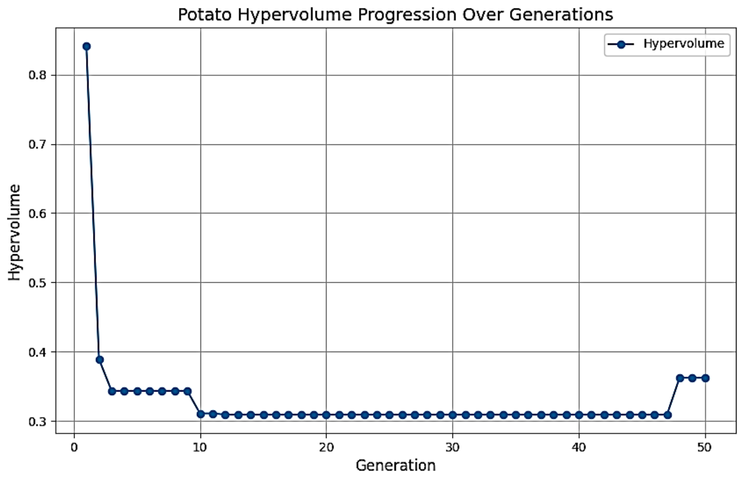

Figure 2: *shows the Hypervolume progression for crop 'Potato, shows the algorithm converges prematurely to suboptimal solutions.*

The simulation results in figure 1 clearly demonstrate the algorithm's tendency to converge prematurely, as shown by the stable hypervolume values from Generation 1 to 18. Initially, in Generation 1, the hypervolume was 0.7426574528111037, however this does not change until Generation 19, suggesting that the algorithm has converged to a local optimum. Despite continued iterations, the hypervolume remains unchanged, illustrating that the algorithm is unable to explore the objective space effectively. This stagnation indicates that the algorithm struggles to escape the local optima, failing to improve the solution further. The results highlight the importance of improving the algorithm's ability to explore the solution space and avoid premature convergence, particularly in complex optimization problems.

In Figure 2, The simulation demonstrates the drop of hypervolume from Generation 1 to Generation 2, and from there, the hypervolume does not improve in the later generations. The algorithm fails to explore solutions relative to the minimum and maximum values of the dataset. The hypervolume indicates the algorithm only focuses on a local optimum which results in possible sub-optimal solutions.

B. Objective of the Study

The objective of the study is to enhance the NSGA-II-Grid-based Crowding Distance Algorithm (NSGA-II-Gr) for resource allocation, specifically tailored for optimizing Rabi crop yield in high-dimensional multi-objective optimization problems.

Specifically, the study aims to accomplish the following:

1. To enhance the algorithm to effectively explore the objective space, while also enabling it to converge to optimal solutions by controlling the spread intensity of solutions as generations progress

II. METHODOLOGY

A. Study Area and Data Collection

The dataset used for this study is from Kaggle, titled "Agricultural Crop Yield in Indian States Dataset". This dataset encompasses agricultural data for multiple crops cultivated across various states in India from the year 1997 till 2020. The dataset provides crucial features related to crop yield prediction, including crop types, crop years, cropping seasons, states, areas under cultivation, production quantities, annual rainfall, fertilizer usage, pesticide usage, and calculated yields.

The researchers also trained the Random Forest Predictive Model for this study. This model is used to get the predicted yield given the area size, and the amount of fertilizer and pesticide. The input is the individual solution which has area, fertilizer, and pesticide. The output is the expected yield from that combination. This is then used to evaluate solutions and serves as the fitness evaluation function for the algorithm. For this study, two crops will be considered: Wheat and Potato. However, other crops from the dataset are tested as well but not shown in this paper

B. Parameters

- Grid Size = 20
- Population Size = 100
- Number of Generations = 50
- Annual Rainfall = 1200 (Constant)

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C. Objectives

- Maximize Yield
- Minimize Area
- Minimize Fertilizer
- Minimize Pesticide

D. Decision Variables

- Area
- Pesticide
- Fertilizer

E. Metrics

Hypervolume is a crucial performance metric in multi-objective optimization, as it measures the volume of the objective space dominated by a set of solutions relative to a reference point. It evaluates both convergence (proximity to the Pareto front) and diversity (spread of solutions). A larger hypervolume indicates better optimization performance, as it reflects a broader and more optimal range of trade-offs between conflicting objectives.

Hypervolume is an essential metric in multi-objective optimization, as it quantifies the objective space dominated by a set of solutions relative to a reference point, reflecting both convergence and diversity. The minimum and maximum values of the fields are used as reference points in this implementation.

In this implementation, hypervolume is computed by first evaluating the population to obtain objective values, followed by dynamic min-max normalization of both the population and reference point to ensure comparability across objectives. Maximized objectives like yield are inverted for consistency with minimization objectives such as area, fertilizer, and pesticide. The normalized population and reference points are then used to calculate the dominated volume via a Hypervolume object, providing a robust measure of the algorithm's ability to explore and exploit the solution space effectively

III. RESULTS AND DISCUSSION

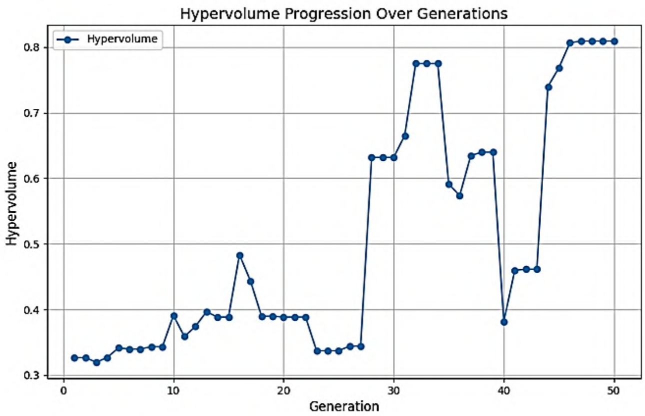

Figure 3: *The result shows that the enhanced algorithm has performed better, especially in higher dimensional problems. In the figure, it has shown that the enhanced algorithm has better results for "wheat crops"*

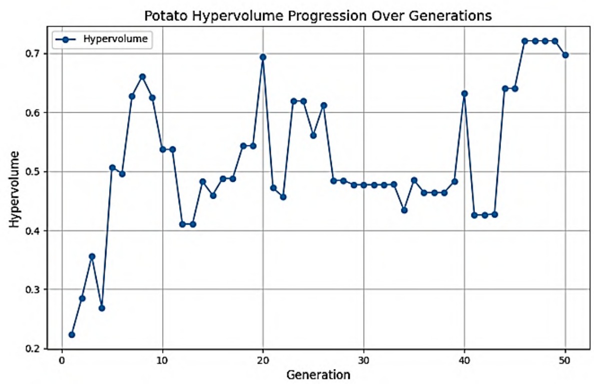

Figure 4: *The result shows that the enhanced algorithm has performed better, especially in higher dimensional problems. In the figure, it has shown that the enhanced algorithm has better results for "potato crops"*

The simulation results in Figure 3 highlight the algorithm's convergence behavior. Initially, the hypervolume starts at 0.3267 in Generation 1 and remains mostly stable until Generation 10, where it increases to 0.3910. A more significant improvement is observed in Generation 16, reaching 0.4834, followed by fluctuations before stabilizing around 0.6317 in Generations 28–30. The hypervolume continues to increase, peaking at 0.8091 from Generation 46 onward. This result shows that while the algorithm experiences periods of stagnation, it eventually escapes local optima and continues improving.

In Figure 2, the simulation initially shows an increasing trend in hypervolume, rising from 0.2234 in Generation 1 to 0.6606 in Generation 8. A notable improvement occurs in Generation 40, reaching 0.6329, followed by another increase to 0.7212 in Generations 46–49 before slightly declining in Generation 50. These results demonstrate the algorithm's ability to explore diverse solutions, as seen in the steady improvement in hypervolume across multiple generations. While some fluctuations occur, the algorithm successfully navigates through different regions of the solution space, ultimately achieving a peak hypervolume of 0.7212. This shows that the algorithm can escape local optima and identify high-quality solutions, showcasing its potential for effective optimization

The enhanced algorithm opens the door for using NSGA-II-Gr in solving high-dimensional problems. The adaptive spreading mechanism gradually increases as the generations progress, allowing the algorithm to further mutate solutions aside from the built-in mutation function. This ensures the algorithm can explore more solutions. The initial algorithm, NSGA-II-Gr, only focused on bi-dimensional problems and was not applied in any real-world problems. In this study, the researchers wanted to explore the use of NSGA-II-Gr in high dimensional problems. Once simulated, the researchers found that the original algorithm suffers from premature convergence, where the solutions stagnate after a few generations and do not improve or change. Also, the original algorithm is not tailored for Rabi crop yield optimization. By implementing an adaptive spreading mechanism and combining a random forest model for fitness evaluation, the researchers addressed the mentioned issues. The resulting improvements will contribute to sustainable and efficient resource allocation practices, ultimately supporting the optimization of Rabi crop yields under real-world agricultural scenarios.

IV. CONCLUSION

The original NSGA-II-Gr algorithm was initially designed for bi-dimensional problems and was not adequately integrated into higher-dimensional problems, such as a 4-objective and 3-variable problem. This limitation often led to premature convergence into sub-optimal solutions. However, through the integration of key modifications, including a modified fitness evaluation process and an adaptive spreading mechanism, the enhanced NSGA-II-Gr algorithm demonstrated its effectiveness in addressing higher-dimensional challenges. Specifically, these enhancements enabled successful applications to optimize Rabi crop yields using the provided dataset. The adaptive spreading mechanism effectively mitigated premature convergence, as evidenced by hypervolume improvements across generations, indicating sustained exploration of the objective space without stagnation. This robust exploration facilitated the discovery of truly optimal solutions. Furthermore, the incorporation of a Random Forest Predictive Model for fitness evaluation established a powerful synergy between genetic algorithms and machine learning, ensuring precise and realistic assessment of solutions based on the dataset. This synergy opens new avenues for research and application, paving the way for data-driven, sustainable solutions in resource optimization and crop yield improvement. This expansion of NSGA-II-Gr for higher-dimensional problems provides a versatile tool for researchers, farmers, and other users to optimize crop yields beyond bi-dimensional problems.

V. RECOMMENDATIONS

Future work could explore additional decision factors, such as annual rainfall, costs, market conditions, or specific attributes like fertilizer and pesticide brands, to further broaden the algorithm's applicability. Other crop types could also be tested in the enhanced algorithm. Additionally, experimenting with alternative fitness evaluation methods may help refine its performance and enhance its capacity to address increasingly complex optimization challenges.

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