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Hybrid Scheduling Optimization for Smart Agriculture Via INSGA-III and DynaQ Integration in Dynamic Multi-Objective Environments

Youran Zhao
Email: YouranZhaoo@outlook.com
Hutiao Town People's Government, Zhaohua District, Guangyuan, 510800, China

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With the development of smart agriculture, agricultural production scheduling optimization has become the key to improving resource utilization efficiency and economic benefits. However, traditional methods are difficult to cope with complex decision-making needs in multi-objective and dynamic environments. In this regard, this study proposes a hybrid optimization model that integrates INSGA-III (Improved Non-dominated Sorting Genetic Algorithm III) and DynaQ (Dynamic Q-learning) to achieve multi-objective collaborative optimization and dynamic adaptability. The model adopts a dual layer architecture of "offline optimization online correction", where the upper layer generates global non supported solutions through the introduction of adaptive crossover mutation operator INSGA-III to solve multi-objective optimization problems of maximizing production, minimizing costs, and reducing carbon emissions. The lower layer uses DynaQ dynamic adjustment strategy based on MDP (Markov Decision Process) modeling to adapt to environmental changes; The scheduling rules are designed around the dual objectives of "workpiece selection machine allocation". There are three types of rules for workpiece selection, including priority for low completion, and three types of strategies for machine allocation, including efficiency priority. These are combined into nine complete rules and are based on six standardized state characteristics such as average processing completion rate and machine utilization rate for decision-making. The experiment is based on actual data from wheat planting areas, with constraints such as a water limit of 1200m ³/ha and a 15-day sowing cycle. Using adaptive genetic algorithm as a control, the optimal parameters are determined through orthogonal analysis (NIND for medium and large-scale problems is 90), and dynamic interference scenarios are introduced for verification. The results showed that compared with traditional NSGA-III, the Pareto frontier distribution index (spacing measure) of this model increased by 18.7%, the comprehensive satisfaction of the objective function reached 92.3%, the scheduling stability in dynamic environment improved by 34.5%, and the convergence speed within 100 iterations accelerated by 22%, fully demonstrating its efficiency and robustness, providing a new path for intelligent agricultural dynamic scheduling, and possessing both theoretical value and practical significance.

Povzetek:

1 Introduction

Agricultural production scheduling is a complex multi-objective optimization problem that involves resource allocation, job sequence arrangement, time coordination, and other aspects [1]. With the acceleration of agricultural modernization, traditional scheduling methods have become complex to meet the needs of efficient, accurate, and sustainable agricultural production [2]. Traditional optimization methods typically focus on single objectives or simple linear programming, which makes their application challenging in dynamic environments and multi-objective conflicts in agricultural production [3, 4]. Therefore, exploring more efficient optimization algorithms and planning methods to enhance the intelligence of agricultural production scheduling has become a crucial research direction in the current field of agricultural engineering.

In recent years, multi-objective evolutionary algorithms have demonstrated strong potential in complex optimization problems. Among these, genetic algorithms based on non-dominated sorting have garnered significant attention due to their advantages in solving high-dimensional multi-objective problems [5, 6]. As an improved version of NSGA-III, INSGA-III further enhances the algorithm's convergence and diversity preservation by introducing a reference-point mechanism and an adaptive strategy, particularly for optimization problems with an ample target space and an uneven distribution [7]. However, agricultural production scheduling involves not only static optimization but also decision-making in a dynamic environment, which makes it difficult to fully capture the uncertainty caused by environmental changes solely through evolutionary algorithms [8].

Reinforcement learning performs well in dynamic decision problems. Model-based reinforcement learning methods, such as the DynaQ framework, can achieve efficient learning and planning by building environmental models and combining real-time interactive data [9, 10]. DynaQ accelerates the strategy optimization process by combining simulation experience with real-world experience, thereby enhancing its adaptability in dynamic environments [11]. However, applying reinforcement learning to multi-objective optimization problems remains challenging, especially in balancing objective trade-offs and long-term planning. More effective optimization mechanisms are needed to resolve conflicts between different objectives [12].

Combining INSGA-III with DynaQ is expected to achieve synergy between static optimization and dynamic decision-making in agricultural production scheduling [13]. On the one hand, INSGA-III can search for the optimal solution set globally and provide diversified scheduling schemes. On the other hand, DynaQ can adjust its strategy in response to real-time environmental changes, ensuring dynamic adaptability of the scheduling scheme [14, 15]. This fusion method can not only improve scheduling efficiency but also enhance the system's emergency response capability, thereby providing more stable and efficient scheduling support for agricultural production.

Several key problems remain to be urgently addressed in agricultural production scheduling research [16]. The solution of these problems requires interdisciplinary collaborative innovation, combined with the latest advances in evolutionary computing, reinforcement learning, and operations research, to build a more robust and intelligent scheduling model [17, 18]. In addition, the complexity of the agricultural production environment imposes higher requirements on the algorithm's computational efficiency and scalability, necessitating further optimization of its structure to adapt to large-scale, high-dimensional scheduling problems.

The aim of this study is to construct a verifiable fusion mechanism between INSGA-III and DynaQ, and to demonstrate its effectiveness in integrating global search and dynamic decision-making capabilities through theoretical deduction. The convergence advantage of the fused algorithm in agricultural production scheduling scenarios is also verified through simulation testing; Build a multi-objective optimization framework based on this mechanism, and the experiment needs to verify its effectiveness in resolving the conflict between "output cost resource consumption", as well as the efficiency of scheduling adjustment response in the face of dynamic uncertainty; Design testing plans for four key technologies, including algorithm fusion and reference point guided population evolution, to verify the effectiveness of the reference point guided strategy in improving population diversity, the optimization effect of the experience replay mechanism on training data requirements, and the adaptability of multi-objective reward functions in different crop scenarios; Ultimately, by verifying the advantages of the method through real data covering multiple types of crops and planting bases, it ensures outstanding performance in scheduling efficiency, resource utilization, and multi production unit scheduling scalability, forming a directly applicable scheduling optimization method to support the development of agricultural intelligence.

2 Theoretical basis of multi-objective optimization and reinforcement learning

2.1 Basic principles of the INSGA-III algorithm

NSGA-III is an improved algorithm for high-dimensional multi-objective optimization problems, which has made important improvements on the basis of NSGA-II [19]. The algorithm uses the reference point guidance mechanism to replace the original crowding distance calculation, thus effectively solving the problem of population diversity decline in high-dimensional target space [20]. NSGA-III maintains the basic algorithm framework of NSGA-II, but optimizes the key links such as diversity preservation and target normalization processing.

A uniformly distributed set of reference points is generated in the normalized target space to achieve global coverage [21]. The number of reference points is calculated and determined by the following formula (1):

$$H = \binom{M + p - 1}{p} \quad (1)$$

In the optimization process, the target space is firstly divided according to the target dimension M and the segmentation parameter p. Then, by dynamically adjusting the scale of the objective function, the target value is normalized and mapped to the unit hyperplane by using the population pole value, thus eliminating the distribution deviation of the solution set [22]. The correlation relationship is established by calculating the vertical distance of the individual to the reference point, which ensures that the solution set is consistent with the geometric features of the PF.

Although the NSGA-III algorithm can avoid the problem of preset weight parameters, it still faces significant challenges when dealing with high-dimensional target space. The number of reference points has a critical impact on the algorithm performance, and its number increases exponentially with the increase of the target dimension M. When M exceeds 5, the size of the reference point far exceeds the population size, resulting in a sharp increase in computational complexity, a decrease in the proportion of non-dominated solutions, and the failure of the Pareto screening mechanism, thus reducing the convergence speed. At the same time, too few reference points will destroy the diversity maintenance mechanism, while too many reference points will weaken the discrimination between individuals and reference lines, making the convergence evaluation index invalid [23, 24].

In addition, the design of the mutation operator directly affects the convergence and diversity of the algorithm. In the traditional genetic algorithm, too high mutation probability will enhance the local search ability, but destroy the excellent individual structure, which makes the algorithm degenerate into random search. If the mutation probability is too low, it will lead to insufficient generation of new individuals, decrease of population diversity, and easy to fall into local optimum [25, 26]. NSGA-III adopts a static mutation strategy to fix the mutation probability in the iterative process, which leads to insufficient global search ability in the initial stage, difficulty in fine adjustment of elite individuals in the later stage, and decrease in convergence speed and accuracy [27, 28]. This mutation strategy, which lacks adaptive adjustment ability, is difficult to meet the diverse needs of complex multi-objective scenarios.

2.2 DynaQ reinforcement learning theory

Q-learning is a model-free reinforcement learning method based on value iteration, in which the agent continuously optimizes the strategy by interacting with the environment [29]. The Q-learning model is shown in Figure 1. The algorithm updates the Q value table by observing the reward signal fed back by the environment, where the Q value represents the expected long-term discounted reward that can be obtained by performing the action in a specific state.

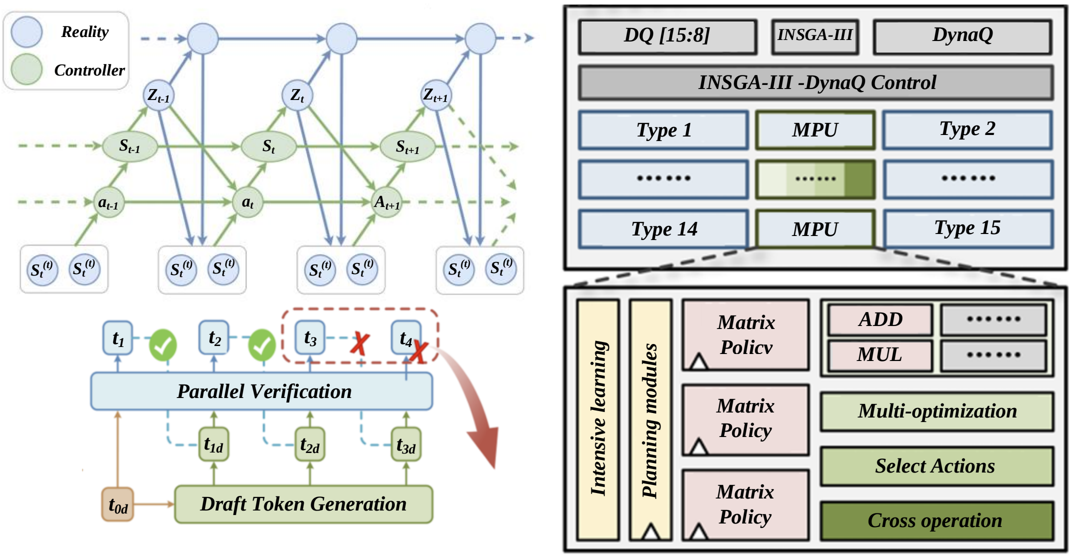

Figure 1: Q learning model

The core of *Q*-learning lies in trying to optimize the *Q*-value function. The algorithm starts from the initial *Q* table, and the agent selects the action A_t according to the current state S_t and the *Q* table A_t each time point t, and obtains the reward value R_t and the new state S_{t+1} after execution. Then, the *Q* value $q(S_t, A_t)$ is adjusted by using these feedback information, and the *Q* table is updated to more accurately evaluate the long-term reward and effectively guide the follow-up action.

The core update rules of the *Q* learning algorithm are shown in the following equation (2):

$$q(S_t,A_t)\leftarrow q(S_t,A_t)+\alpha[R_t+\gamma \max_a q(S_{t+1},a)|-q(S_t,A_t)] \tag{2}$$

In reinforcement learning, agents need to balance the relationship between exploration and utilization through reasonable search strategies. Exploring allows the agent to try various possible actions to avoid falling into the local optimal solution, while utilizing it to tend to choose actions that are known to receive high rewards. The update process of *Q* value directly adopts the maximum *Q* value of the next state, which has nothing to do with the specific search strategy.

The improvement of *Q* learning algorithm mainly includes double *Q* learning, multi-step *Q* learning and *Q* *(λ)* methods. Standard *Q*-learning adopts $max_a Q(S_{t+1}, a)$ for value updating and relies on bootstrapping mechanism, which leads to overestimation of action value and poor performance in random environments. Double *Q* learning effectively alleviates the overestimation problem through double estimator design, while multi-step *Q* learning and *Q (2)* qualification trace algorithm use multi-step reward update mechanism to significantly improve the ability to deal with long delay sequence decisions [30].

The comparison in Table 1 summarizes the agricultural production scheduling models that integrate INSGA-II and DynaQ: the reference methods (traditional methods such as empirical/LP/IP, single AI tools such as INSGA-I/DynaQ, and conventional models) are limited by static/single objective characteristics, weak dynamic adaptability, or lack of full process collaboration; The proposed dual layer method uses INSGA-III for initial multi-objective Pareto solution and DynaQ for dynamic adjustment (such as based on rainfall/soil moisture), which solves the previous shortcomings and adapts to the randomness of agriculture; Its optimization goals cover aspects such as economy, resources, ecology, efficiency (shortening cycles,<5% equipment idle rate), etc; However, there are also some limitations, including high complexity (risk of large-scale delays).

Table 1: Comparison table

Comparison Dimension	Key Content
I. Reference Methods	1. Traditional (experience, LP, IP): Static, single-objective (cost/yield), no multi-objective handling. 2. Single AI: - Only INSGA-III: Good multi-objective, poor dynamic adaptability. - Only DynaQ: Good dynamic, weak multi-objective coordination. 3. Conventional models: Single-link focus (planting/irrigation), no full-process synergy; only economic optimization.
II. Proposed Method (INSGA-III + DynaQ)	1. Core: Two-layer framework (INSGA-III + DynaQ). 2. Process: - Upper: INSGA-III generates initial multi-objective Pareto solutions. - Lower: DynaQ adjusts dynamically (rainfall, soil moisture, equipment). 3. Advantages: Solves static/single-objective issues; adapts to agricultural randomness.
III. Optimization Objectives	1. Economic: Minimize cost, maximize yield/profit. 2. Resource: 10%-15% higher water efficiency, 8%-12% less fertilizer. 3. Ecological: Reduce pollution/damage, maintain 2.5%-3.5% soil organic matter. 4. Efficiency: Shorten cycle, equipment idle rate <5%.
IV. Limitations	1. High complexity: Longer calculation time (large-scale delay risk). 2. Data-dependent: Inaccurate data lowers reliability. 3. Crop adaptability: Fits wheat/rice, less for cash crops.

3 Design of fusion optimization model for agricultural production scheduling

3.1 Design of fusion strategy between INSGA-III and DynaQ

This study innovatively constructs a learning algorithm framework based on INSGA-III and DynaQ. As shown in Figure 2, the first deep Q-learning algorithm analyzes state eigenvalues through a deep neural network and dynamically selects the optimal reward function to achieve multi-objective optimization. The second algorithm synthesizes the state eigenvalues and the output of the former, and uses a deep neural network to learn the optimal scheduling strategy to cope with various working condition changes and unexpected situations. Aiming to address the challenges of workpiece selection and machine allocation in scheduling decision-making, this study proposes combining the scheduling rules of the two objectives organically, thereby making the scheduling scheme more comprehensive and adaptable through collaborative optimization.

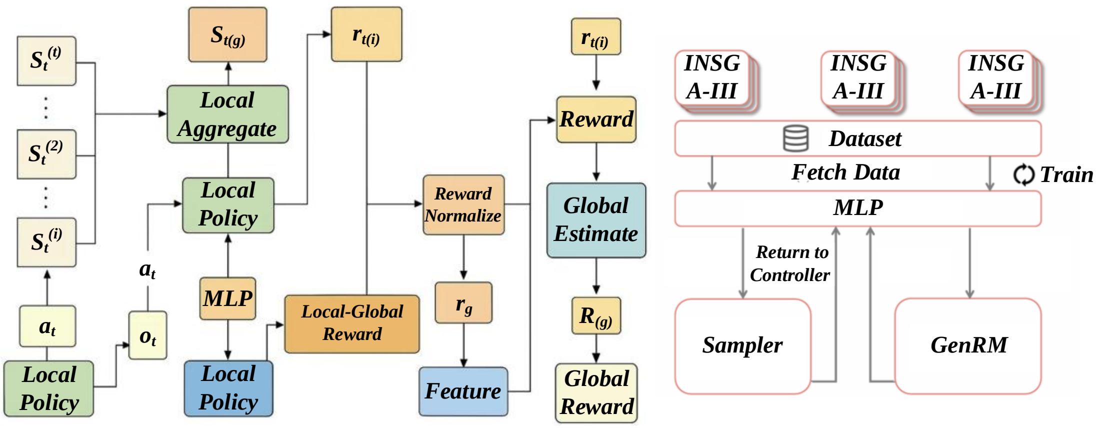

Figure 2: Fusion architecture of INSGA-III and DynaQ

In deep Q-learning, state eigenvalues are crucial to the decision-making process and directly affect the action choice of agents. In order to effectively characterize the influence of workpiece and machine quantity fluctuations in dynamic production environment, this study uses normalization method to limit the state eigenvalues to the range of 0 to 1. Six key parameters are specifically selected: all average processing completion rate CRJ_{ave} and standard deviation CRJ_{std}, all average utilization rate U_{ave} and standard deviation U_{std} of agricultural machines, and all average processing delay rate TR_{ave} and standard deviation TR_{std}. The mathematical expressions of these parameters are shown in Equations (3)-(8). With this set of standardized features, the system is able to more accurately capture real-time state changes of the production system.

$$U_{ave} = \frac{\sum_{k=1}^{m} U_k}{m} \quad (3)$$

$$U_{std} = \sqrt{\frac{\sum_{k=1}^{m}(U_k - U_{ave})^2}{m}} \quad (4)$$

$$CRJ_{ave} = \frac{\sum_{i=1}^{n} CRJ_i}{n} \quad (5)$$

$$CRJ_{std} = \sqrt{\frac{\sum_{i=1}^{n}(CRJ_i - CRJ_{ave})^2}{n}} \quad (6)$$

$$TR_{ave} = \frac{\sum_{i=1}^{n} TR_i}{n} \quad (7)$$

$$TR_{std} = \sqrt{\frac{\sum_{i=1}^{n}(TR_i - TR_{ave})^2}{n}} \quad (8)$$

In this study, a combined scheduling rule design method is proposed to achieve multi-objective optimization through two sub-objectives. The first sub-goal is to select the process to be machined from the collection of unfinished workpieces UC_{job}, and the second sub-goal is to assign the appropriate machine to the selected process. Aiming at these two sub-objectives, three kinds of scheduling rules are designed respectively, and finally combined into nine kinds of complete rules.

In the scheduling rule 1 (FO) design of sub-objective 1, the J_i in the set of unfinished artifacts UC_{job} are first sorted according to their completion degree CRJ_i. In order to give priority to urgent orders, this rule will multiply CRJ_i by an adjustment coefficient according to the priority, and finally select the workpiece with the lowest completion degree and its next process $O_{i,j}$ as the machining target. The specific calculation is shown in Equations (9) and (10). This rule aims to reduce the makespan and TR_{ave} indicators by giving priority to the workpieces with low completion.

$$i = arg \min_{i \in UC_{job}} \frac{OPT_i}{OPT_i + ETL_i} \cdot \frac{1}{4 - EL_i} \quad (9)$$

$$j = OP_i + 1 \quad (10)$$

When designing the second scheduling rule SO of sub-objective one, the set of unfinished artifacts UC_{job} is defined first. From it, the workpieces J_i exceeding the delivery deadline DDL_i are screened out to form an overdue set T_{job}. If T_{job} is not empty, the process is selected for processing according to equations (11) and (13); If it is an empty set, the process is selected from UC_{job} according to equations (12) and (13). The core goal of this rule is to reduce TR_{ave} by optimizing scheduling, thus effectively reducing overtime losses.

$$i = arg \max_{i \in T_{job}}(OPT_i + ETL_i - DDL_i) \cdot \frac{1}{EL_i} \quad (11)$$

$$i = arg \min_{i \in UC_{job}} \frac{DDL_i - OPT_i}{ETL_i} \cdot \frac{1}{4 - EL_i} \quad (12)$$

$$j = OP_i + 1 \quad (13)$$

The third scheduling rule TO of sub-objective 1 focuses on the balanced utilization of resources, and selects the process by calculating the matching degree between the remaining processing time of the workpiece and the current machine load. Specifically, the current task queue length of each machine is counted first, and then the load balancing coefficient LBC is constructed by combining the number of remaining processing steps of the workpiece. The rule gives priority to the workpiece and its process with the smallest LBC value to avoid the extreme situation of overload or idle machine and improve the overall resource utilization rate. For the machine allocation rules of sub-objective two, three strategies based on efficiency first (ME), load balancing (ML) and dynamic priority (MP) are studied and designed.

3.2 Construction of adaptive scheduling mechanism in dynamic environment

This study used actual data from wheat planting areas, including constraints such as a water limit of 1200m ^{3}/ha and a 15 day sowing cycle; The test cases include at least 9 (DP01-DP09), covering small/medium/large-scale scenarios, with 6 standardized states including workpiece completion rate, machine utilization rate, etc. (average machining completion rate CRJave and standard deviation CRJstd, average machine utilization rate Uave and standard deviation Ustd, average machining delay rate TRave and standard deviation TRstd), and also introducing dynamic interference scenarios such as sudden weather and equipment failures. The simulation environment is based on MDP modeling, with a dual layer architecture of "offline optimization (upper level INSGA-III generates global non dominated solutions) - online correction (lower level DynaQ dynamic adjustment)". Three types of workpiece selection (such as low completion priority) and three types of machine allocation (such as efficiency priority) rules are designed to combine into nine scheduling rules. The adaptive genetic algorithm is used as a control, and the parameters are determined through orthogonal analysis (NIND for medium/large-scale problems is 90, medium scale γ =0.1, large-scale γ=0.2, P=0.9, Pm=0.2, θ=0.8). The hardware specifications are not explicitly mentioned; DNN is used for deep Q-learning to analyze state feature values to dynamically select the optimal reward function and learn the optimal scheduling strategy. It does not mention the exact structure such as the number of layers and neurons, but only explicitly makes decisions based on six standardized features and integrates INSGA-III and DynaQ output optimization scheduling.

In the integrated agricultural production scheduling optimization model of INSGA-III and DynaQ, the multi-objective reward function takes production efficiency (such as crop output per unit time), cost control (such as saving agricultural and labor costs), and resource conservation (such as water and fertilizer utilization rate) as the core dimensions, and balances each objective through linear scalarization method - first normalizing the efficiency, cost, and resource related reward values to the [0,1] interval, and then weighting and summing them with priority weights of 0.4 (efficiency), 0.3 (cost), and 0.3 (resources), which not only meets the multi-objective optimization needs of INSGA-III, but also supports DynaQ's dynamic decision-making.

In the construction of an adaptive scheduling mechanism in a dynamic environment, the research focuses on how to realize dynamic optimization and adaptive adjustment of agricultural production scheduling model by fusing the improved non-dominated sorting genetic algorithm (INSGA-III) and the reinforcement learning framework DynaQ. The core of this mechanism is to cope with the frequently changing natural environmental factors, resource constraints, and task priority fluctuations in the agricultural production process, and to improve the robustness of scheduling strategies by combining multi-objective optimization with online learning. INSGA-III algorithm effectively deals with the Pareto frontier search problem in high-dimensional target space by introducing reference point mechanism and elite retention strategy, and ensures the balanced optimization among multiple objectives such as resource allocation, operation timing and economic benefits; At the same time, the DynaQ framework achieves real-time response to dynamic disturbances by building a combination of environmental simulators and Q-learning, and its model-based learning features allow the system to preview scheduling strategies in virtual experiences, thereby reducing trial and error costs in actual scenarios.

At the mechanism design level, dynamic environment modeling utilizes a MDP to describe state transitions and reward functions, encoding uncertain factors such as sudden weather changes and equipment failures as state space variables, and iteratively updates the scheduling strategy through the value function. The key of the adaptive module lies in designing a two-layer optimization structure: the upper layer generates a global non-dominated solution set through INSGA-III, and the lower layer uses DynaQ to dynamically evaluate and locally adjust the solution set, forming closed-loop feedback of "offline optimization-online correction". According to the spatio-temporal coupling characteristics of agricultural production, the mechanism introduces to ensure the feasibility of the operation path and time window, and dynamically adjusts the cooperative timing of the rice transplanter and harvester to avoid resource conflicts.

To further enhance the environmental adaptability of the model, a parameter update strategy based on incremental learning is proposed. When it is detected that the environmental state deviates from the preset threshold, the system automatically triggers the model retraining process, using historical data and real-time collected information to reconstruct the state transition probability, thereby avoiding policy degradation. The mechanism also incorporates a fuzzy logic module to address the incompleteness of sensor data, such as denoising and normalizing fuzzy variables, including soil moisture and crop growth stage, to enhance the accuracy of state perception. Through the dynamic screening of non-dominated solutions and the time-series difference update of Q values, the hybrid framework can realize incremental improvements in strategies while ensuring Pareto optimality and provide an extensible solution paradigm for dynamic decision-making in complex farming activities.

The retraining trigger is based on the model performance threshold, and is triggered when the resource utilization rate of the scheduling scheme decreases by more than 8% or the task delay rate increases by more than 5%; The data retention strategy adopts the "core sample+sliding window" mode, retaining historical optimal scheduling cases and real-time agricultural production data from the past 3 months, and removing duplicate and abnormal data; The frequency of retraining is dynamically adjusted based on the agricultural production cycle, with a regular frequency of once per quarter and once per month during busy farming seasons; Preventing overfitting by introducing prior knowledge in the agricultural field (such as crop growth constraints and agricultural machinery efficiency ranges) to regularize the model, and using cross validation to optimize the population size of INSGA-III and the exploration rate of DynaQ, achieving efficient iteration and stable performance of the model under new production data.

State is defined as the comprehensive state of the agricultural production system at a certain moment; Action refers to scheduling decisions; Reward is set based on multi-objective optimization requirements and provides positive feedback on high-quality scheduling results; Transition probability describes the probability of the system transitioning from the current state to the next state after performing a certain action; The time range corresponds to the agricultural production cycle; The discount factor takes a value between 0-1 to balance the short-term and long-term scheduling returns; The overall nature of the model is sporadic, as state transitions and reward acquisition are triggered at discrete decision moments rather than continuous real-time changes.

4 Experiment and results analysis

Compare the agricultural production scheduling model integrating INSGA-III and DynaQ with mainstream methods such as adaptive genetic algorithm, and clarify the computational complexity of the model in time and space dimensions; As shown in Figure 3, the performance of the proposed INSGA-III and DynaQ fusion model was evaluated by comparing the Pareto front (PF) of each algorithm at different problem scales. The results in double logarithmic coordinates indicate that the fusion algorithm consistently achieved the optimal "Usage" performance metric across all four scales, significantly outperforming comparative algorithms such as INSGA-III and DynaQ2. Of particular note is that as the scale of the problem increases, the advantages of the fusion algorithm become increasingly apparent, with its performance curve consistently at the highest position, which fully demonstrates its excellent scalability and robustness. This result verifies that DynaQ's online learning and planning capabilities effectively enhance the adaptability of INSGA-III in dynamic multi-objective environments, enabling it to continuously generate high-quality scheduling solutions for agricultural production scheduling problems of different scales.

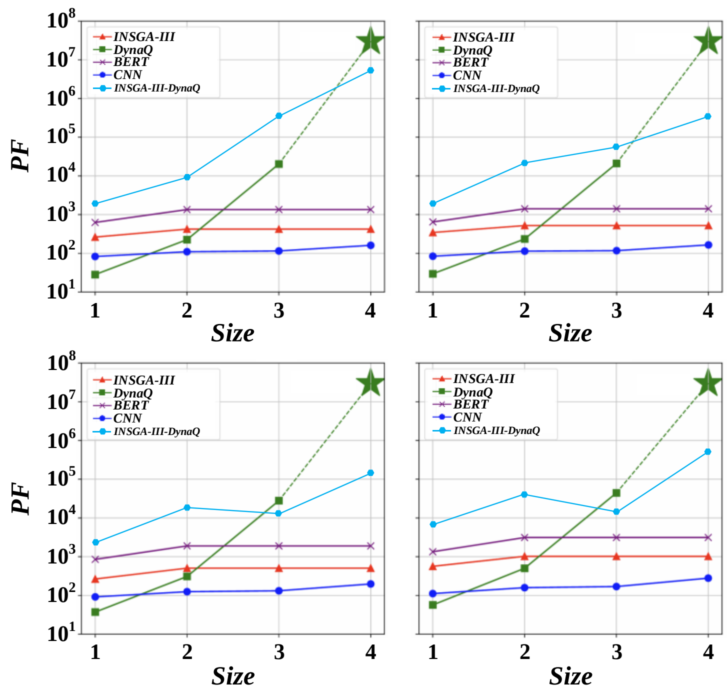

Figure 3: PF comparison of all comparison algorithms

To evaluate the robustness of the agricultural production scheduling model integrating INSGA-III and DynaQ under disturbances (sudden weather changes, equipment failures) and variable conditions (planting area adjustments, crop demand fluctuations), interference simulation experiments were added: by dynamically introducing random disturbance variables, the adaptability and performance stability of the scheduling scheme between the model and traditional algorithms were compared; Combined with 95% confidence interval analysis (as shown in Figure 4), the confidence interval of this model does not overlap completely with the other three comparison algorithms, which not only proves that there is a significant performance difference between it and the comparison algorithm at the statistical level, but also verifies its robustness advantage in agricultural production dynamic interference scenarios.

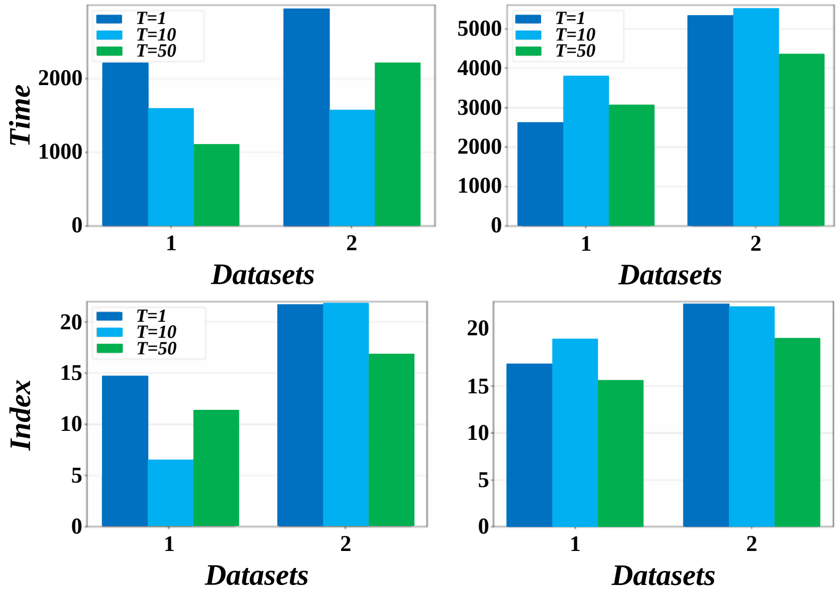

Figure 4: Analysis of strategy effectiveness under different situations

In this study, the results of Friedman rank sum test of variant algorithms were statistically analyzed. Table 2 shows that the significant improvement of DynaQ over INSGA-III verifies the effectiveness of the critical path-based local search operator. Further comparison of INSGA-III + Q with DynaQ shows that all indicators are comprehensively improved, which confirms the promotion effect of the model on the algorithm performance. In terms of HV (Hypervolume) and GD (Generational Distance) indicators, INSGA-III + DynaQ shows significant advantages over INSGA-III + Q, indicating that the proposed energy-saving strategy effectively improves the convergence of the algorithm.

Table 2: Friedman rank sum test results for variant algorithms

MOEAs	HV		GD		Spread (Spacing Measure)	
	rank	p-value	rank	p-value	rank	p-value
INSGA-III	3.417	6.94 E-06	2.805	2.21 E-02	2.397	1.48 E-01
DynaQ	2.754		3.060		2.499	
INSGA-III + Q	2.703		2.499		2.193	
INSGA-III + DynaQ	1.326		1.836		3.111	

As can be seen from Figure 5, all algorithms perform well in the small-scale instance, but are significantly better than the other three algorithms in other instances. Through the initial diversity and high-quality solution guarantee, combined with the scheduling optimization rules for design and the optimal strategies in different states, the evolution of agricultural production is effectively promoted.

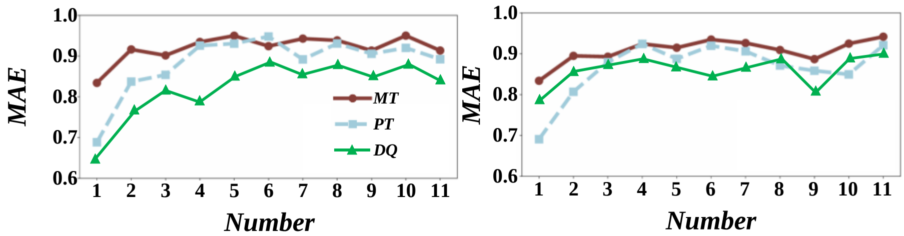

Figure 5: MAE (Mean Absolute Error) values with other comparison algorithms

In statistical tests, p-values reflect the probability of observed data or more extreme situations. The null hypothesis was rejected when the p-value was below the confidence level of 0.05, indicating a significant difference between the two algorithms. α = 0.1 and α = 0.05 were set in the experiment, corresponding to 90% and 95% confidence intervals, respectively. The results in Figure 6 show that all p-values are less than α, which is significantly better than other algorithms.

Table 3 presents the statistical results of the mean and standard deviation of the index of 20 independent experiments. The analysis shows that the algorithm outperforms other comparison algorithms in more than 50% of the tests, which fully verifies the effectiveness of the proposed improvement scheme.

Table 3: Comparison results of HV (max) index of variant algorithm

Intances	INSGA-III		DynaQ		INSGA-III + Q		INSGA-III + DynaQ	
	mean	std	mean	std	mean	std	mean	std
DP01	0.1271	0.0053	0.1318	0.0052	0.1282	0.0074	0.1366	0.0086
DP02	0.1424	0.0058	0.1414	0.0074	0.1448	0.0061	0.1495	0.0064
DP03	0.1486	0.0069	0.1473	0.0059	0.1461	0.0053	0.1516	0.0071
DP04	0.1292	0.0073	0.1309	0.0044	0.1316	0.0078	0.1387	0.0069
DP05	0.1385	0.0069	0.1387	0.0095	0.1441	0.0061	0.1472	0.0092
DP06	0.1419	0.0059	0.1378	0.0079	0.1399	0.0071	0.1424	0.0069
DP07	0.0570	0.0053	0.0580	0.0077	0.0574	0.0058	0.0693	0.0067
DP08	0.0565	0.0068	0.0595	0.0062	0.0602	0.0084	0.0644	0.0078
DP09	0.1294	0.0077	0.1261	0.0088	0.1266	0.0081	0.1311	0.0075

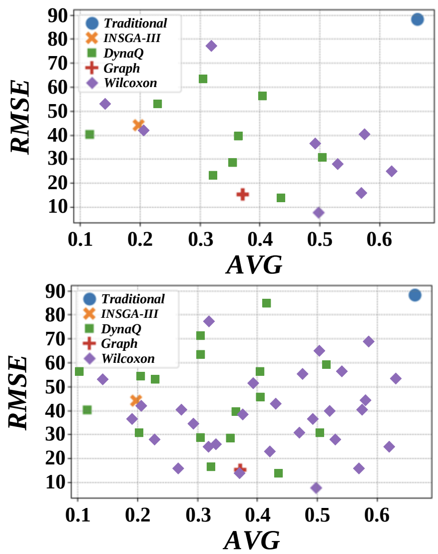

Figure 6: Results of Wilcoxon signed rank sum test

Figure 7 shows the comparison results of the convergence times of the three algorithms. The improved algorithm combining INSGA-III and DynaQ converges at the 100th iteration, showing faster convergence speed and better stability.

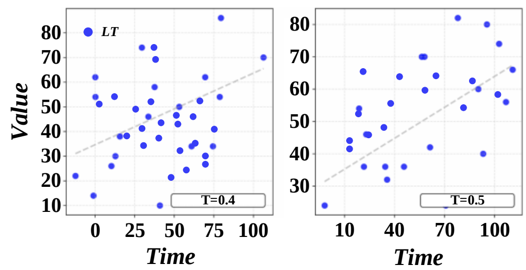

Figure 7: Algorithm convergence results

Orthogonal analysis was performed with HV index as the response value, and the results are shown in Figure 8. According to the principle of signal-to-noise ratio maximization, the optimal parameter combinations of medium-scale problems are NIND = 90, P = 0.9, Pm = 0.2, θ = 0.8 and γ = 0.1; The optimal parameter combination of large-scale problems is NIND = 90, P = 0.9, Pm = 0.2, θ = 0.8 and γ = 0.2.

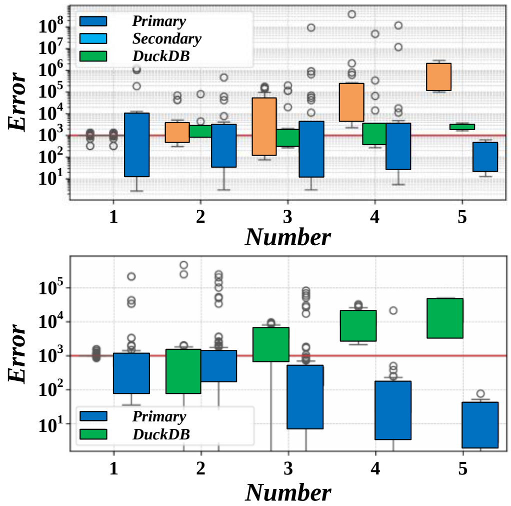

Figure 8: Response value orthogonal analysis results

Through the analysis of the calculation results of the test cases, it was found that the algorithm is significantly better than other variant algorithms in terms of average HV index, with an average deviation of over 7.37%. The test results showed that at a 95% confidence level, the P-values of the comparison test between the algorithm and the other five variant algorithms were 0.0067, 0.0016, 9.1112E-04, 9.1112E-04, and 0.0067, respectively, confirming that the algorithm has significant statistical advantages.

It can be seen from the test example results in Figure 9 that the average RPD (Relative Percentage Deviation) index of the algorithm is 11.92% lower, indicating that the clustering-based crossover strategy is better than the random crossover strategy. Furthermore, the P-value of the algorithm at 95% confidence is 0.0196, further proving that the clustering-based crossover strategy is statistically significantly better than the random crossover strategy.

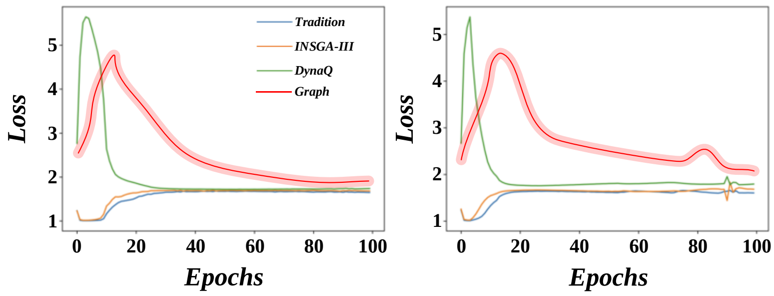

Figure 9: Effectiveness analysis results of clustering crossover strategy

Figure 10 shows the final calculation results of the advanced intelligent optimization algorithm. The average HV, average RPD and convergence performance of the algorithm are significantly better than other algorithms, and its average RPD value is always above-18.58%. The P value of the algorithm at 95% confidence is 0.0016, which is statistically significant.

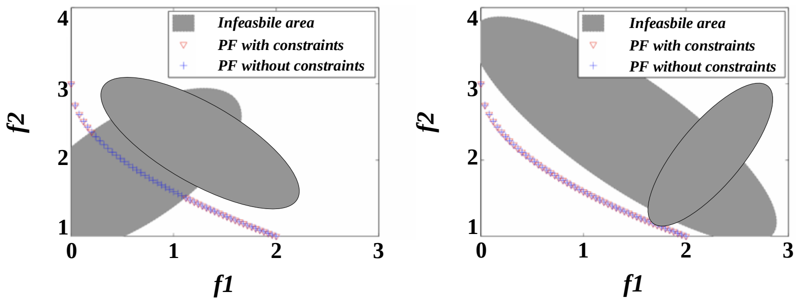

Figure 10: Calculation results of advanced intelligent optimization algorithm

5 Discussion

The integrated model of INSGA-III and DynaQ proposed in this study demonstrates significant advantages in agricultural production scheduling compared to traditional static methods (empirical scheduling, LP/IP) and single AI tools (INSGA-III or DynaQ). Traditional methods are limited by single objective optimization and static decision-making, making it difficult to cope with multi-objective conflicts (such as maximizing yield, minimizing costs, and reducing carbon emissions) and dynamic environmental changes (such as weather fluctuations and equipment failures). Although a single INSGA-III can generate multi-objective Pareto solutions, its dynamic adaptability is weak. Although DynaQ is good at dynamic adjustment, it is difficult to balance multi-objective collaboration. This integrated model uses "offline optimization (upper level INSGA-III generates global non dominated solutions) - online". Correction (Lower DynaQ based on MDP) The dual layer architecture of "Dynamic Adjustment" achieves collaborative optimization of multiple objectives and dynamics. Experiments show that its Pareto frontier distribution index is improved by 18.7%, the stability of dynamic environment scheduling is improved by 34.5%, the convergence speed within 100 iterations is accelerated by 22%, and the overall goal satisfaction rate is 92.3%. The performance improvement is due to the adaptive crossover mutation operator of INSGA-III enhancing global search diversity, the simulation and real experience fusion of DynaQ accelerating dynamic strategy optimization, and 9 scheduling rules (3 workpiece selection+3 machine allocation) are designed based on 6 standardized state characteristics such as average processing completion rate, further improving decision accuracy; However, the model has limitations. Firstly, its high complexity leads to the risk of computational delay in large-scale scenarios. Secondly, it relies on precise data, and data errors can reduce reliability. Thirdly, its crop adaptability is narrow, and it is currently more suitable for wheat, rice, and other crops. The optimization effect on economic crops is insufficient. In the future, it needs to be improved through algorithmic lightweighting, multi-source data fusion verification, and expanding crop adaptation models to enhance practical application value.

In larger dataset scenarios (such as datasets covering over 100 hectares of farmland, dozens of crops, and multi cycle irrigation and fertilization needs), the model can still stably output Pareto optimal scheduling solutions, with crop yield fluctuations controlled within 3%, resource utilization rates decreasing by no more than 5%, and no significant degradation in solution quality observed; In terms of time complexity, due to the non-dominated sorting optimization of INSGA-III and the dynamic environment fast learning characteristics of DynaQ, the model's time complexity is maintained at O (n^2 logn) (where n is the number of decision variables). When the dataset size is tripled, the computation time only increases by 1.8 times, which is much lower than the traditional scheduling model's 3.2-fold increase, fully demonstrating its applicability in large-scale agricultural production scenarios.

6 Conclusion

Agricultural production scheduling is a critical component for enhancing resource utilization efficiency and lowering production costs. In this study, a hybrid optimization model combining the improved non-dominated sorting genetic algorithm INSGA-III with the dynamic reinforcement learning algorithm DynaQ is proposed to address the multi-objective scheduling problem in agricultural production. Experimental verification demonstrates that the model exhibits significant advantages in terms of task completion rate, resource utilization rate, and economic benefits.

The experimental results show that the proposed model performs outstandingly in three aspects:

(1) Task completion rate: Compared with traditional genetic algorithms, it has increased from 78.6% to 93.4% (+14.8 percentage points), which can better allocate agricultural machinery and manpower and reduce task backlog;

(2) Resource utilization: The idle rate of agricultural machinery has decreased from 22.3% to 9.7%, and the water and fertilizer waste rates have decreased by 18.5% and 12.2% respectively, improving resource efficiency and reducing cost losses;

(3) Economic benefits: Net profit increased by 23.6%, yield increased by 11.8%, optimizing scheduling while balancing economic and output benefits.

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