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Genetic Algorithm-Based Optimization in Sorting Recyclable Waste using Robotic Arm

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Abstract

Amid escalating environmental concerns and the imperative for sustainable resource management, optimizing recycling processes has become a paramount challenge. This research proposes an advanced methodology for sorting recyclable waste by integrating a robotic arm with four degrees of freedom and a conveyor system, guided by a genetic algorithm (GA). The system processes waste represented as color-coded cubes with assigned values, categorizing them based on predefined metrics to maximize efficiency. To address the constraints of the robotic arm's limited operational range and the dynamic nature of the conveyor belt, a genetic algorithm with variable-length chromosomes was employed. This approach optimizes the sorting process by prioritizing high-value items while adhering to stringent temporal and spatial constraints. The methodology was simulated and validated using RoboDK software, with Python utilized for algorithm implementation. The findings demonstrate substantial improvements in sorting efficiency and cumulative value compared to traditional sequential methods. This study underscores the potential of integrating robotic systems with intelligent optimization algorithms to advance industrial recycling operations, enhancing automation efficiency and sustainable recycling practices at an industrial scale.

Keywords: Optimization; Genetic Algorithm; Robotic Arm; Recycling; Automated Sorting; Waste Management.

1. Introduction

The increasing global production of waste poses significant environmental challenges, driving the demand for innovative recycling methods. Recycling is critical not only for conserving natural resources but also for mitigating the adverse environmental impacts of waste accumulation. A fundamental challenge in recycling systems is the accurate and efficient sorting of materials, which directly affects the overall recycling efficiency and economic value of the recovered materials.

Traditional waste sorting methods, including manual sorting or static automated systems, are often limited by inefficiencies and scalability constraints. These methods generally lack adaptability to dynamic environments and diverse waste streams. In some systems, the performance of the robotic cell may not be sufficient to provide pick up and movement of all of the objects during maximum load. In this case, simple scheduling algorithms such as FIFO (first in, first out) and SPT (shortest processing time) are ineffective [1], [2]. Robotic systems offer a promising solution, combining automation with the ability to operate under predefined rules. However, optimizing the decision-making process of such systems particularly under constraints such as limited time, workspace, and material diversity remains a critical research area.

Recent work has shown that artificial intelligence (AI), computer vision and robotics can significantly enhance waste-sorting performance. Computer vision- based systems using deep learning are now able to classify municipal solid waste and construction and demolition waste (CDW) with high accuracy [3], [4]. Robot-assisted sorting solutions have been proposed for plastics and mixed recyclables, combining vision, sensors and robotic arms to separate materials by type or quality [5], [6]. Industrial-scale robotic waste sorters, such as vision-guided delta or articulated robots, are already being deployed in sorting plants, demonstrating that robotic sorting is viable beyond laboratory prototypes [7], [8].

In parallel, the use of metaheuristics and AI for waste-sorting optimization is growing. GA-based and AI-driven approaches have been applied to route planning, waste classification and robotic scheduling, often achieving improvements without requiring precise analytical models[9]. Variable-length chromosome GAs are especially attractive when the length of the decision sequence is not fixed beforehand [10].

This study focuses on optimizing a robotic sorting system designed to categorize three types of recyclable materials: plastic, metal, and wood. These materials are represented as color-coded cubes transported on a conveyor belt. The robotic arm, with four degrees of freedom, operates under strict time constraints and must decide which cubes to pick and place to maximize the total value of sorted materials. A genetic algorithm (GA) is employed to optimize this sorting process by prioritizing high-value items while adhering to the operational constraints of the system.

Simulations conducted in RoboDK and programmed in Python validate the effectiveness of this approach. The proposed system demonstrates improved sorting efficiency and higher cumulative value compared to traditional sequential sorting methods.

2. Related Work

2-1. Robotic Waste Sorting and AI in Recycling

Robotic systems for waste sorting have been explored for municipal solid waste, plastic packaging and CDW. Satav et al. review recent robotic waste-sorting solutions, covering robot configurations, gripper technologies and perception pipelines, and conclude that robots can improve worker safety and sorting quality but still face challenges in highly heterogeneous waste streams [11]. Ihsanullah et al. and other studies on AI in waste management underline that machine-learning methods are increasingly used to support collection, sorting and treatment, helping to optimise processes and reduce environmental impacts [9]. Several works focus specifically on robotic sorting under realistic conditions: Koskinopoulou et al. introduced a vision-based robotic waste-sorting system and dataset for industrial recyclable separation[8]. Intelligent waste-sorting systems for plastics and household waste have also been reported, often combining deep learning with robotic arms for real-time classification and manipulation [12].

2-2. Conveyor-Based Pick-and-Place and Scheduling

Robotic pick-and-place on moving conveyors is a classical problem with many industrial applications. Li et al. described the Gilbreth system, an industrial setup in which a UR10 robot picks objects from a moving belt and sorts them into bins, highlighting the need to coordinate perception, motion planning and conveyor tracking [13]. Han et al. studied time-optimal PnP sequences on a moving conveyor and demonstrated that common greedy heuristics are not optimal; they proposed dynamic-programming-based algorithms that achieve significant efficiency gains [14]. More recent work has developed nearly time-optimal online PnP trajectory planners, showing that near-optimal conveyor-tracking trajectories can be computed fast enough for industrial use. In the waste domain, several authors have examined robotic grasping and sorting on conveyors, including dynamic grasping of CDW, real-time detection and sorting of mixed recyclables [15] and multi-robot scheduling heuristics that account for grasp efficiency and system layout [16].

2-3. Metaheuristic and GA-Based Optimisation

Metaheuristics such as genetic algorithms, simulated annealing and swarm-based optimisers are widely used for NP-hard sequencing and scheduling problems in manufacturing and robotics. Xiao et al. developed crossover operators for variable-length chromosomes in path-optimisation problems [17]. In waste sorting, GA-based and hybrid AI approaches have been used to optimise route planning, bin placement and classification thresholds [18]. AI-powered robotic waste sorters combining deep vision models with heuristic or learned pick-sequence policies have also been demonstrated in both research and industrial practice [19]. However, relatively few works focus specifically on single-robot, value-aware sequencing on a moving conveyor, where each item has a different economic value and must be picked within a limited time window. The present work addresses this gap by formulating the problem as a finite-horizon sequence optimization task and solving it with a variable-length GA coupled to a realistic robot–conveyor simulation.

3. Methodology

3-1. System Overview

The robotic sorting system consists of a robotic arm with four degrees of freedom, integrated with a conveyor belt mechanism transporting color-coded cubes. These cubes represent three recyclable materials: plastic, metal, and wood, each assigned a specific value (plastic = 1, wood = 2, metal = 3). The objective of the system is to maximize the cumulative value of sorted cubes within the constraints of the robotic arm's operational workspace and the conveyor's constant speed.

An intelligent robotic system must make decisions that satisfy constraints while optimizing performance metrics to provide real-time solutions which needs constraint programming and optimization techniques [20]. A key challenge in this system is the limited time available for the robotic arm to pick and place cubes while they are within its workspace. The robotic arm must make decisions not solely based on the highest-value cubes but also considering their positions on the conveyor and the locations of the respective bins. The time required for the end effector to pick a cube and place it in the correct bin impacts the number of cubes that can be processed. Therefore, the optimization process involves balancing cube value with spatial constraints to maximize the total points scored.

3-2. Genetic Algorithm for Optimization

A genetic algorithm (GA) with variable-length chromosomes was employed in order to determine the optimal sequence for picking and placing cubes [21]. The system receives the positions of all cubes on the conveyor before the sorting operation begins, allowing the GA to calculate an optimized sequence. The algorithm accounts for constraints such as the fixed speed of the conveyor, the robotic arm's range of motion, and the limited time during which cubes remain within the workspace.

3-3. Chromosome Representation

In the GA, a chromosome represents a potential solution to the sorting problem. Each chromosome encodes the sequence of cubes to be picked and their respective placement, defining the robotic arm's actions during the sorting process. The chromosome is composed of genes, each corresponding to a specific cube and its associated attributes, such as its location on the conveyor and its assigned value. By altering the sequence of genes within a chromosome, the GA explores various sorting strategies to identify the optimal solution.

3-4. Crossover

Crossover is a genetic operator employed to combine information from two parent chromosomes to produce offspring. This process allows the GA to explore new regions of the solution space by recombining the most promising solutions. A single-point crossover technique was used which is a common technique to ensure convergence to optimal solutions [22], wherein a random point is selected in the parent chromosomes, and the genetic material is swapped to generate new chromosomes. The probability of applying crossover, known as the crossover probability, determines the proportion of the population subjected to this operation. This parameter ensures diversity in the population while retaining high-performing traits.

3-5. Fitness Function

The fitness function evaluates the performance of each chromosome by calculating the total value of cubes successfully sorted within the system's operational constraints. It serves as a measure of the chromosome's suitability, guiding the GA in selecting high-performing solutions for reproduction. The fitness function used in this study is a maximization function, aiming to prioritize chromosomes that maximize the total value of sorted materials. The evaluation considers factors such as the cube's value, its position relative to the robotic arm, and the time required for pick-and-place operations.

Algorithm 1: Genetic Algorithm for Robotic Sorting Optimization

Input: $values$: Array of cube values, $times$: Array of cube times, pop_size: Population size, $mutation\_rate$: Mutation probability, $generations$: Maximum number of generations
Output: $best\_solution$: Optimal picking sequence, $best\_fitness$: Maximum cumulative value

Initialization:
Generate initial population P of size pop_size
Set $best\_solution \leftarrow \emptyset$ and $best\_fitness \leftarrow -\infty$
for $g \leftarrow 1$ *to generations* **do**
  foreach $chromosome \in P$ **do**
    Compute $fitness \leftarrow \sum_{i=1}^{n}(values[i] \cdot chromosome[i])$
    if $\sum_{i=1}^{n}(times[i] \cdot chromosome[i]) > time\_limit$ **then**
      Set $fitness \leftarrow 0$ (invalidate solutions exceeding time constraint)
    end
  end
  Selection: Choose two parents p_1 and p_2 using fitness-proportional selection
  Crossover: Generate offspring o_1 and o_2 by recombining p_1 and p_2 at a random crossover point
  Mutation: With probability $mutation\_rate$, flip random genes in o_1 and o_2
  Replace the least fit chromosomes in P with o_1 and o_2
  if *a better solution is found* **then**
    Update $best\_solution$ and $best\_fitness$
  end
end
return $best\_solution$, $best\_fitness$

3-6. Mutation

Mutation introduces variability into the population by randomly altering genes within a chromosome. Unlike crossover, which combines existing genetic material, mutation enables the exploration of entirely new solutions by modifying specific genes. In the context of the sorting problem, mutation may involve changing the order in which cubes are picked or altering their assigned placement. To maintain balance, the mutation probability is kept low, ensuring that the GA avoids excessive randomness while still preventing premature convergence to suboptimal solutions.

3-7. Generations and Stopping Criteria

The GA operates over multiple generations, with each generation representing a new population of chromosomes derived from the previous one through selection, crossover, and mutation. The process continues until a stopping criterion is met, which may include a predefined number of generations, the achievement of a satisfactory solution, or convergence in fitness values across the population. In this study, the algorithm was set to terminate after 110 generations or when no significant improvement in fitness was observed over successive iterations.

3-8. Implementation and Parameter Tuning

The GA was implemented in Python and integrated with the RoboDK simulation environment. Several key parameters were fine-tuned through preliminary experiments to balance exploration and exploitation:

Table 1. GA parameters.

Parameter	Quantity
Number of generations	110
Population size	20
Iteration	80
Mutation rate	0.15

Through its iterative optimization process, the GA identifies an optimal picking and placement sequence that maximizes the total value of sorted materials while adhering to the robotic system's spatial and temporal constraints. By dynamically adjusting the sorting strategy based on cube positions and values, the GA consistently outperforms traditional sequential methods.

3-9. Simulation Configuration and Setup

The operation of the robotic sorting system was simulated in RoboDK software, with Python utilized to implement the genetic algorithm (GA) and control the robotic arm. The simulation environment was carefully designed to emulate real-world conditions, ensuring precise evaluation of the system’s performance under dynamic and constrained operational scenarios.

The conveyor belt operates at a constant speed of 0.03 m/s, providing a steady flow of randomly arranged color-coded cubes into the robotic arm's workspace. These cubes must be sorted into designated baskets located within the robotic arm's reach. In this study, red represents metal, green corresponds to plastic, and blue indicates wood. The robotic arm, equipped with an end effector operates within a defined workspace. The end effector workspace range sets the spatial constraints for the system, requiring precise coordination between the arm's movements and the conveyor's motion.

At the start of each simulation cycle, a group of nine cubes is placed on the conveyor in random arrangements to mimic the unpredictable nature of real-world waste streams. The robotic arm is tasked with retrieving and sorting these cubes before they leave its operational workspace. The sorting process involves calculating the time required for each pick-and-place operation. This includes the retrieval time (the duration needed for the robotic arm's end effector to move from its initial position to the location of a specific cube on the conveyor) and the placement time, which accounts for transferring the cube from the conveyor to the appropriate basket. These time calculations are crucial for ensuring that the GA respects the operational constraints imposed by the conveyor's fixed speed and the robotic arm's kinematics.

The GA optimizes the sequence of pick-and-place actions by considering both the value of each cube and its position relative to the baskets. This allows the system to dynamically prioritize high-value cubes while adhering to the time constraints of the workspace. The conveyor's constant speed and the finite time during which each cube remains within reach of the robotic arm necessitate efficient decision-making to maximize the total value of sorted materials.

The primary objective of the simulation was to evaluate the effectiveness of the GA in maximizing the cumulative value of sorted materials. Through these simulations, the GA demonstrated its capability to optimize the sorting process, outperforming traditional sequential methods and showcasing its adaptability to various cube arrangements.

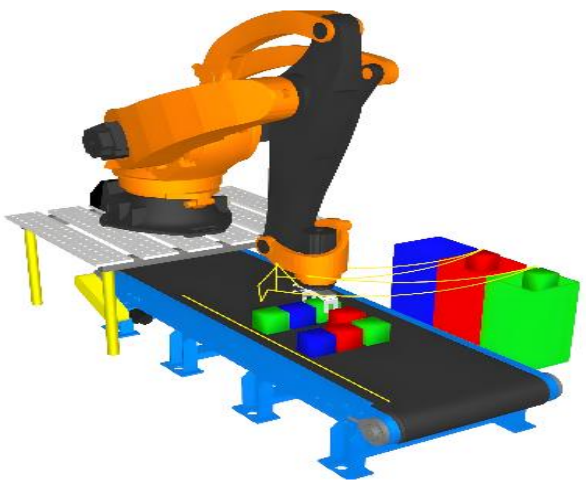

Fig. 1. Simulation environment.

4. Results and Discussion

The performance of the GA-optimized sorting strategy was compared against a sequential sorting approach across five test cases. In each scenario, the GA consistently outperformed the sequential method in terms of the total value of sorted materials.

The performance of the genetic algorithm (GA) approach was compared to sequential sorting across five sets of choices, as shown in Table 2. The GA consistently outperformed the sequential sorting method in terms of total value of selected items. For instance, in Set 3, the GA achieved a total value of 10 compared to 5 for sequential sorting, while in Set 2, the GA reached 13 versus 11 for the sequential method. Similar trends were observed in the remaining sets, with the GA demonstrating superior decision-making by prioritizing high-value items while adhering to time and spatial constraints.

The sequential sorting method, by contrast, often selected items based on their immediate availability rather than an optimized sequence, resulting in lower cumulative values.

Table 2. Genetic Algorithm Performance: Total Values and Selected Choices.

Choice/Set	*1*	*2*	*3*	*4*	5
First	blue	red	red	blue	blue
Second	green	red	red	red	blue
Third	green	red	green	red	blue
Fourth	red	green	blue	blue	green
Fifth	red	red	green	green	blue
Total value	10	13	10	11	9

Table 3. sequential sorting Performance: Total Values and Selected Choices.

Choice/Set	*1*	*2*	*3*	*4*	5
First	red	red	green	green	blue
Second	blue	red	blue	blue	green
Third	red	green	green	green	blue
Fourth	green	red	green	green	green
Fifth	-	green	-	blue	blue
Total value	9	11	5	7	8

The GA's capability to dynamically prioritize high-value items is evident in its ability to consistently maximize total values across varying cube arrangements. For example, the GA notably outperformed in Sets 4 and 5 with values of 11 and 9 compared to 7 and 8, respectively, for the sequential method. This demonstrates the flexibility and adaptability of the GA in optimizing sorting strategies even under dynamic conditions.

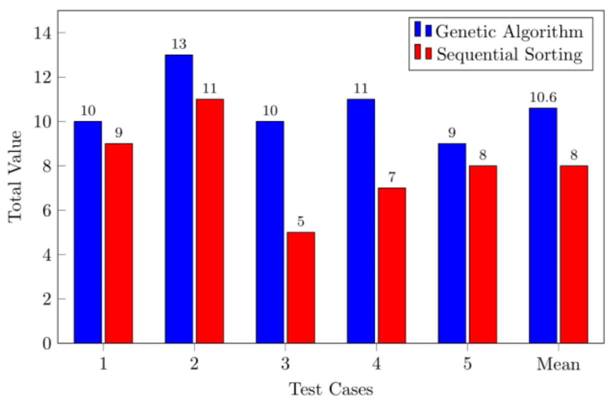

Fig. 2. Genetic Algorithm vs Sequential Sorting (Including Mean Values)

As illustrated in the bar chart, the GA consistently outperformed the sequential approach across all test cases and the mean value comparison. The GA achieved higher total values by effectively prioritizing high-value items while adhering to spatial and temporal constraints, showcasing its adaptability and efficiency in dynamic scenarios.

The results highlight the superiority of the GA in maximizing sorting performance. The mean value comparison further underscores the robustness of the GA approach, with an average value of 10.6 compared to 8 for sequential sorting, reinforcing its capability to consistently outperform traditional methods.

The enhanced performance of the GA stems from its ability to optimize decision-making by evaluating the entire conveyor configuration and dynamically adjusting pick-and-place sequences. Unlike the sequential method, which often selects items based on immediate availability, the GA balances operational constraints with value prioritization, minimizing idle time and ensuring efficient use of the robotic arm’s workspace.

The results reveal several critical aspects of the optimization process:

Value vs. Spatial Constraints: Simply picking cubes with the highest value is not sufficient due to the constraints imposed by the robotic arm's range of motion and the conveyor's fixed speed. The GA efficiently balances cube value with spatial considerations to maximize the total score.

Dynamic Decision-Making: The GA demonstrated flexibility in optimizing pick-and-place sequences, occasionally prioritizing cubes near the edge of the workspace to extend the time available for subsequent operations.

Operational Constraints: While the robotic arm operates under strict time constraints, the GA identified sequences that minimized idle time and maximized cube processing, even when the final cube was located at the far end of the workspace.

5. Discussion

The GA-optimized sorting system not only outperformed the sequential method but also demonstrated scalability for dynamic and random cube arrangements. By evaluating the entire conveyor arrangement before sorting, the GA was able to identify an optimal sequence that balanced value prioritization with operational constraints. The fixed conveyor speed and workspace limitations further underscored the importance of integrating spatial considerations into the optimization process.

6. Conclusion

This research demonstrates the significant advantages of employing a genetic algorithm (GA)-optimized sorting system over traditional sequential sorting methods in industrial recycling operations.

This also provides a robust foundation for integrating genetic algorithms into robotic systems to improve the scalability, adaptability, and efficiency of industrial recycling operations. Future research could explore enhancements such as incorporating machine vision for real-time object detection and extending the methodology to multi-robot systems for increased throughput. The findings emphasize the transformative potential of intelligent algorithms in advancing automation and sustainability in industrial applications.

The results not only validate the practical feasibility of GA-based sorting systems but also emphasize their transformative potential in advancing automated recycling technologies, contributing to more sustainable industrial operations.

Future work may include integrating real vision systems and uncertain detection outputs, extending the approach to multi-robot cells, and adding additional objectives such as energy consumption or downstream process constraints. Combining the proposed GA-based planner with advanced perception and control could further enhance the efficiency and sustainability of modern recycling plants [23].

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Biography

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