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Original Article

Robotic Process Optimization Using Evolutionary Algorithms

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ABSTRACT

Industrial robotics plays a vital role in modern automation across industries such as automotive, aerospace, healthcare, agriculture, and defense. However, optimizing robotic processes remains challenging due to objectives like reducing energy consumption, minimizing cycle time, improving accuracy, and handling dynamic operating conditions. Traditional optimization methods often struggle with these complex problems. Evolutionary Algorithms (EAs) such as Genetic Algorithms (GA), Differential Evolution (DE), Evolution Strategies (ES), and Multi-Objective Evolutionary Algorithms (MOEA) provide effective solutions for robotic optimization. These techniques are widely used in robotic path planning, task scheduling, trajectory optimization, and resource management. Simulation results show that evolutionary algorithms improve operational efficiency, reduce collisions, minimize energy consumption, and optimize productivity better than conventional methods. Genetic Algorithms are effective for trajectory optimization, while Differential Evolution offers faster convergence in continuous optimization tasks. Multi-objective approaches achieve balanced trade-offs between productivity and energy efficiency. The study highlights the importance of evolutionary algorithms in developing intelligent and adaptive robotic systems for Industry 4.0. Future work includes hybrid optimization models, deep reinforcement learning integration, and real-time distributed robotic optimization.

KEYWORDS

Robotic Process Optimization, Evolutionary Computation, Genetic Algorithm, Industrial Robotics, Motion Planning, Multi-objective Optimization, Intelligent Automation, Adaptive Robotics.

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1. INTRODUCTION

1.1. Background

In recent years, robotics is one of the most dominant technologies contributing to the industrial automation and manufacturing production systems to change the way they work. There are many applications that are using industrial robots, including packaging, painting, quality inspection, material handling, welding, and assembly, where high precision, consistency, and speed are desired. These robotic systems are highly effective in increasing productivity, decreasing human resources, and improving workplace safety by reducing repetitive and risky tasks and reducing error. The overall efficiency of robotic systems is not only dependent upon mechanical design and control architecture, however, it is also dependent upon the optimization of the operational processes of the robots. Robotic process optimization involves optimizing key process parameters like motion path, actuator efficiency, task sequencing, energy efficiency, control strategies to maximize productivity and minimize the operational cost and resources. In real world applications, robotic systems may be required to function in dynamic and uncertain environments in which nonlinearities in the system behavior, sensor noise, external disturbances, and conflicting objectives make for complex optimization problems. In these scenarios, the use of conventional optimization methods like linear programming, gradient based or deterministic search methods may fail to provide reliable solutions, as they are prone to getting stuck in local minima and computational constraints. The problems that have to be faced have been met with the introduction of evolutionary algorithms as powerful optimization tool. They can be used for global search, adapt to varying conditions, and solve nonlinear optimization problems without the need for gradient information, making them very appropriate for advanced robotic process optimization.

1.2. Need for Evolutionary Algorithms in Robotics

With the speed of the development of robotic technology, the complexity of robotic systems has grown significantly, and the optimization method should be intelligent and adaptive. Today's robots are required to work in challenging, uncertain, and highly interactive environments, rather than just in simple, repetitive tasks. Such systems are required to handle the enormous volumes of sensor data, to be able to make decisions in real time, to cooperate with other robots and to adapt to the changes of the operational environment. Optimization solutions based on the classical methods are challenging to apply to such complexities because of the presence of multiple conflicting objectives, large search space, and the presence of nonlinear system behavior. Evolutionary algorithms are effective solutions, because they are capable of good global optimisation and adaptive search mechanisms. They are able to search multiple solutions in parallel, making them well suited to modern robotic applications.

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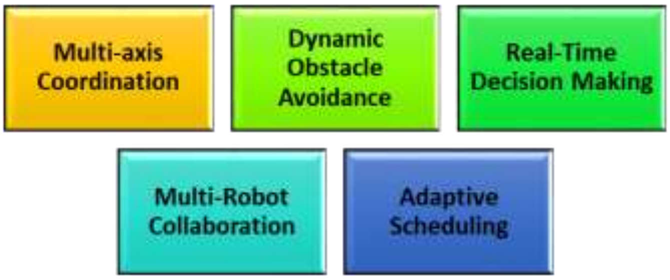

Fig 1 - Need For Evolutionary Algorithms in Robotics

1.2.1. Multi-axis Coordination

Most modern industrial and service robots have multiple degree of freedom (DOF), which involves the simultaneous precise coordination of several degree of freedom of the robot's joints and actuators. Robotic manipulators require each axis to move in sync to maintain accurate positioning, smooth motion and efficient task execution. The more axes one has, the more complex the motion planning and control becomes. Multiple motion patterns are explored in order to optimize the joint movements, trajectory planning, and actuator coordination, using evolutionary algorithms. This allows robots to execute more complicated operations like assembly, welding, and material handling more precisely while also minimizing mechanical strain.

1.2.2. Dynamic Obstacle Avoidance

Real world robotic systems are often faced with obstacles that are moving, changing workspace conditions, and unexpected interruptions. Real-time obstacle detection and generation of new motion plans is essential for safe and efficient robot operation. In such environments, where the environment may change rapidly or multiple obstacles exist, traditional path planning methods may become ineffective. EAs have adaptive search capabilities that enable robots to find paths in which they do not collide with other robots and remain efficient in their movement. This is particularly useful for autonomous navigation, robotics for warehouses, and mobile robots.

1.2.3. Real-Time Decision Making

There are many robotic applications that involve real-time decisions in time-critical and uncertain environments. Medical robots, industrial robots, and autonomous robots need to be able to adapt their behavior based on the information they receive from sensors, as well as the changes in their environment. Real-time optimization can be achieved using evolutionary algorithms that continually process potential solutions and determine the best action to take. This allows robots to handle unforeseen circumstances, enhance their operational reliability, and ensure consistent performance even in complex settings.

1.2.4. Multi-Robot Collaboration

In a high level of automation systems a number of robots are able to collaborate for accomplishing a common task, which can be assembly, transportation, collaborative inspection, etc. There needs to be a coordination of task allocation, communication, motion synchronizing, and conflict avoidance for effective collaboration. Coordination becomes increasingly complex, as the number of robots grows. In the case of multiple robots optimizing task distribution and movement planning, evolutionary algorithms ensure a balanced distribution of the workloads and efficient use of the resources. This enables greater system productivity and minimizes delay in an environment of collaborative robot systems.

1.2.5. Adaptive Scheduling

Changing priorities of tasks, machine availability and production requirements are common in Robotic production systems. Static scheduling techniques might not be resilient to such fluctuations and hence results in inefficiency and production delays. Evolutionary algorithms can be used for adaptive scheduling, and dynamically modify the task sequence and resource allocation as they are operating. It enables robotic systems to stay productive, minimize downtime, and maximize manufacturing efficiency under the ever changing industrial environment.

1.3. Robotic Process Optimization Using Evolutionary Algorithms

Evolutionary algorithms in the field of robotic process optimization have proven to be a sophisticated solution to enhance the performance, efficiency, and intelligence of contemporary robotic systems. The complexity of operations using robots has grown considerably as its applications in industrial automation, healthcare, logistics, aerospace, agriculture and autonomous systems continue to grow. In dynamic and uncertain environments, robots must navigate to complete a task, generate motion, optimize the generated path, schedule the task, calibrate their sensors, and control themselves adaptively. These tasks frequently have nonlinear behavior, are subject to multiple constraints, and involve conflicting objectives, such as minimizing execution time, while maximizing accuracy, energy efficiency, etc. Common optimization techniques are often difficult to use in this context as they rely on gradients, a simplified mathematical model or a known operating condition. Another class of algorithms suitable for such problems are evolutionary algorithms, which rely on population-based search techniques that mimic natural evolution and biological adaptation. A number of algorithms like Genetic Algorithms (GA), Differential Evolution (DE), Particle Swarm Optimization (PSO) and multi-objective evolutionary approaches (MOEA) are successfully used in robotic optimization problems. The algorithms start with a population of candidate solutions, which can include various combinations of robotic operating parameters, including joint angles, actuator velocities, sequences of tasks, or control variables. The algorithms then perform operations of selection, mutation, crosses and survival of the best solutions in an iterative manner, leading to better and better solution quality over the course of several generations. This allows robots to find efficient paths, minimize the risk of collision, minimize energy consumption and maximize task completion time. In industrial use, evolutionary optimization has been able to increase production rate, decrease operational expenses and increase the reliability of the systems. For autonomous mobile robots, these algorithms can be used for intelligent navigation, obstacle avoidance, and adaptive decision-making in real-time scenarios. Moreover, multi-objective evolutionary algorithms can optimize multiple competing objectives, like speed, safety, and precision, to achieve a more balanced and viable solution. The application of evolutionary algorithms in robotic process optimization thus not not only optimizes operations but also contributes to designing intelligent, autonomous, and self-adaptive robotic systems that can effectively manage complex real-world scenarios.

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2. *LITERATURE SURVEY*

2.1. Early Optimization Approaches

The main research efforts on robot optimization were devoted to classical deterministic optimization approaches to enhance robot performance, motion efficiency and task scheduling. Dynamic programming, branch and bound optimization, and gradient based search algorithms were extensively used in industrial robotics and automated-control systems. Dynamic programming proved to be very helpful for solving the problems with sequential decision making, one in which the actions of a robot could be decomposed into smaller subproblems and solved recursively. For combinatorial optimization problems like task sequencing, assembly planning and workspace allocation, branch-and-bound methods were used to narrow the search space without compromising on optimality. Optimization procedures such as gradient descent were frequently employed for minimizing the difference between the measured and predicted variables, for tuning the parameters, for optimizing the controller and for refining the trajectory. These methods worked well for solving problems in controlled and low dimensional settings, but were constrained in their application to real world robotic systems. Deterministic approaches could be costly and generally failed to cope with the nonlinear and multi-modal search spaces that increasingly encountered in robotic environments, and were sensitive to initial conditions. The limitations led to greater need for more adaptive and robust optimization strategies.

2.2. Genetic Algorithm-Based Optimization

Genetic Algorithms (GAs) were an important development in the field of robotic optimization research. GAs were inspired by the ideas of natural selection and biological evolution, and provided a population-based search mechanism that could search for solutions in large, complex solution spaces. They used the genetic algorithm approach to solve various robotic problems such as path planning, motion scheduling, manipulator control and autonomous navigation. GAs were used for robots to discover near-optimal paths that accounted for several operational constraints as obstacle avoidance, smoothness of robot motion, energy consumption, and travel time in robotic path planning. Genetic algorithms could jump out of local optima via the crossover, mutation and selection operations to provide more globally optimal solutions, unlike the deterministic methods. Prior to 2019, studies have shown that GA-based optimization can greatly enhance the performance of robotic systems in manufacturing and service applications. The experimental results demonstrated the advantages of this approach, including shorter operational cycle times, smoother trajectory generation, and enhanced adaptability in the presence of uncertainty. In addition, GAs proved to be an effective optimisation method for multi-parameter robotic systems where traditional analytical solutions were not easily obtainable, and were one of the most popular evolutionary methods used for optimising robotic processes.

2.3. Differential Evolution in Robotics

Another evolved optimization method that has become popular is Differential Evolution (DE), which is well suited for robots with continuous parameters for optimization. DE had an attractive implementation structure, converged fast and required less number of control parameters than genetic algorithm, and thus was more easily applied to engineering problems. The researchers applied differential evolution to the control of a robotic manipulator, trajectory generation, sensor calibration, and optimization of the inverse kinematics. For robotic motion planning, DE facilitated smooth tuning of joint parameters and motion paths for achieving accurate motion control with minimal mechanical stress and energy consumption. The important advantage of DE is that it is able to search a large solution space efficiently without premature convergence. This was especially applicable to nonlinear robot optimization problems in which several feasible solutions are possible. DE assisted in tasks such as sensor calibration to achieve more accurate measurement results by optimizing the alignment of sensors and parameters used to compensate for errors. The introduction of robotics systems with increasing complexity and the need for real-time optimization of these systems led to the popularity of differential evolution as a computational efficient approach in terms of obtaining high quality solutions within reasonable time.

2.4. Multi-objective Evolutionary Algorithms

The number of applications in advanced manufacturing, healthcare, logistics, and autonomous systems all saw robotic optimization begin to involve more than one objective, with these objectives often conflicting. This gave rise to the use of Multi-Objective Evolutionary Algorithms (MOEAs) that are able to optimize multiple objectives simultaneously and balance them. Typically, the goals in robotics are speed, accuracy, energy efficiency, productivity, safety, and trajectory smoothness. Traditional optimization methods have not been very useful in solving such a trade-off; however, MOEAs introduced the concept of Pareto optimality, and researchers were able to find multiple non-dominated solutions. NSGA-II, Strength Pareto Evolutionary Algorithm 2 (SPEA2), and Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) were among the algorithms that gained popularity in the field of robotic optimization research. The algorithms enabled engineers to work on other solutions and choose the best operating condition for the specific application. MOEAs enhanced production efficiency with reduced energy use in industrial robotics, and optimized the speed of navigation with localization error and obstacle avoidance in autonomous robots. Multi-objective Evolutionary Algorithms (MOEAs) has been instrumental in the improvement of the flexibility, intelligence and adaptability of modern robotic systems.

3. METHODOLOGY

3.1. System Model

The proposed robotic optimization framework aims to enhance the performance, efficiency, and intelligence of robotic processes by incorporating evolutionary computation methods into the optimization and control of robots. A series of interdependent stages make up the system, with each stage helping to determine an optimal solution for the robotic task execution. This overall framework is composed of the acquisition of the input parameters, the robot process modeling, the fitness evaluation, the evolutionary search operations and the selection of the final solution.

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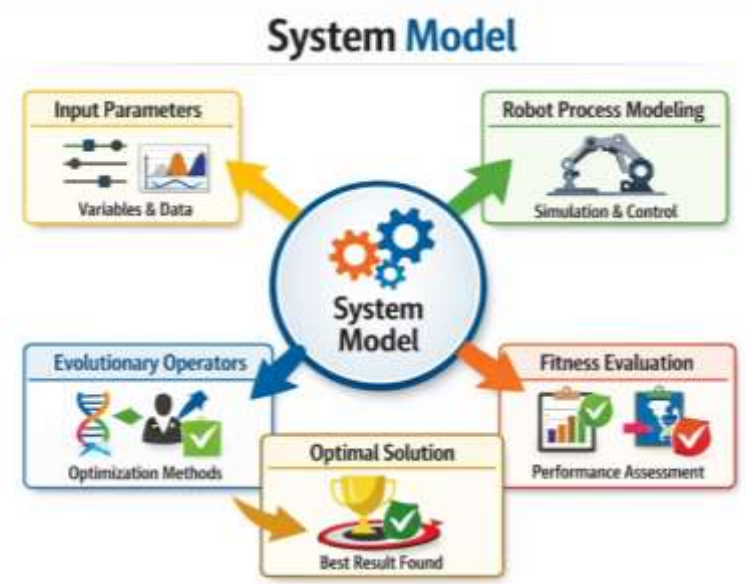

Fig 2 - System Model

3.1.1. Input Parameters

The first part of the system model is input parameters collection and definition needed for the robotic optimization. These parameters are physical, operational and environmental parameters that will affect the performance of the robot. Common parameters are joint angles, actuator speed, payload weight, energy limits, workspace size, obstacles position and task execution constraints. Furthermore, the correct parameters for the process (e.g. cycle time requirements, precision tolerance, safety boundaries etc.) are taken into account. The values of these variables are the starting point of the optimization algorithm and directly influence the quality of the solutions obtained. Correct parameters would make the optimization process representative of actual operating conditions and yield practical solutions.

3.1.2. Robot Process Modeling

Once input is acquired, the robotic system is mathematically and computationally modeled so it can simulate the behavior of the robot when performing the task. This stage involves in capturing the kinematic structure, dynamic properties, motion constraints and interaction of the robot with the surrounding environment. The process model represents the robot's movements, tasks to be executed and reaction to the operational conditions. The model takes into account factors like trajectory generation, collision avoidance, torque bounds and smooth movement. This enables the development of a realistic portrayal of the robotic process which serves as the basis for testing candidate solutions during optimization. If the process is well designed, the simulation model could be made more accurate and the outcome of the optimization would be more reliable.

3.1.3. Fitness Evaluation

The fitness evaluation stage assesses the quality and effectiveness of the candidate solutions created throughout the optimization process. In this stage, execution time, energy consumption,

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positional error, path smoothness and avoiding collisions are examined as performance metrics. All proposed solutions are evaluated in terms of their ability to meet the specification optimization goals and constraints. Solutions that result in improved performance of the robot get higher fitness scores, less efficient or unsafe solutions get less fitness scores. The evaluation mechanism can steer the search process to provide increasingly effective answers over successive searches, and provide a way to give feedback and improve the process itself.

3.1.4. Evolutionary Operators

After computing fitness values, the evolutionary operators are used to create better candidate solutions. The operators are based on natural evolutionary processes and usually consist of selection, crossover, mutation and population replacement. Selection chooses those solutions that work best for reproduction and crossover takes various characteristics from different solutions to form new ones. Random variability from mutation keeps diversity, prevents premature convergence. The algorithm is able to search the space efficiently and incrementally improve over the course of repeated uses of these operators. The process of evolution searches for the optimum operation conditions, even under complex and nonlinear environments.

3.1.5. Optimal Solution

The last stage of the system model is the choice of the most optimal solution with several iterations of optimization. This optimal solution is the most efficient set of robotic parameters, which meet the specified goals and conditions. Depending on the application, the selected solution can consist of optimized trajectories, optimized joint movements, optimized task scheduling patterns or optimized control parameters. The best solution is then applied in the robotic system to increase the efficiency of the operations, lower the energy requirements, increase the accuracy and shorten the execution time. The final output will allow for the robot to be more productive and reliable in real-world industrial environments.

3.2. Genetic Algorithm Framework

In the proposed robotic optimization system the Genetic Algorithm (GA) framework is used in order to seek out the best solutions in complex and multi-dimensional environments. GA seeks to emulate the natural evolutionary process of selection and reproduction of candidate solutions in an iterative fashion. The algorithm can be applied in robotic systems for optimizing operating parameters like motion trajectories, work scheduling, energy efficiency and productivity of the process. The optimization process consists of a series of sequential stages: Population initialization, Fitness evaluation, Selection and genetic operations.

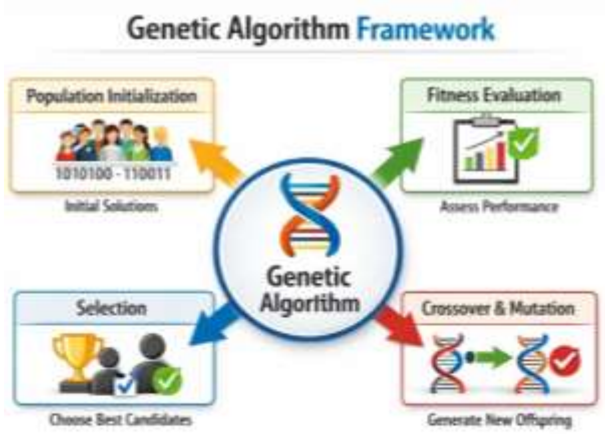

Fig 3 - Genetic Algorithm Framework

3.2.1. Population Initialization

The first step of the genetic algorithm is to create a starting set of possible solutions, called the population. A set of parameters for a robotic process, typically referred to as a chromosome, are encoded in each candidate solution.A set of parameters for a robotic process, often referred to as a chromosome, is encoded into each candidate solution. They are usually solutions that are randomly generated within certain operating limits in order to broaden the search space. Population diversity is important as it enables the algorithm to investigate a variety of possible solutions, instead of just a limited area. During robotic optimization, an optimized initial population has a higher chance of being able to find efficient and feasible solutions in subsequent generations. This stage is the initial step of the evolution search process.

3.2.2. Fitness Evaluation

After the initial population is generated, each candidate solution is tested with a fitness function to determine the effectiveness of the solution in achieving the optimization goal. The fitness evaluation in the robotic system takes into account productivity, energy consumption and safety. Productivity is the measure of how efficiently the robot is able to execute the set tasks, energy is the power the robot uses when it's moving, and safety is how well the robot can operate without colliding with other robots or moving in unsafe ways. These factors are then used to calculate fitness value of each candidate solution using the fitness function. The solutions which have the better fitness values imply that they are more efficient in operation and more suitable to survive in the evolutionary process. This stage is crucial in the development of the algorithm for achieving the best robotic performance. $f(x)=\alpha P+\beta E+\gamma S$

3.2.4. Selection

Once fitness evaluation, the algorithm chooses the best candidate solutions for reproduction. Within this context the tournament selection is used as selection strategy. Tournament selection: A small number of solutions is selected at random from the population and the one with the highest fitness score is selected for the next generation. This process is repeated until the desired number of parent solutions is found. Tournament selection is a combination of exploration-exploitation by

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selecting the best solutions and enabling other less dominant solutions to come out in the competition. In robot optimization, this ensures diversity in the population and steadily evolves the quality of the solutions through generations.

3.2.5. Crossover and Mutation

The parent solutions that are selected are subjected to mutation and crossover operations to create new offspring solutions. At cross over, segments of two parent chromosomes mix together to produce new candidate solutions which contain features from both parents. This process can enable advantageous characteristics such as effective motion patterns or low energy configurations to be transmitted to the next generation. The mutation adds a small random change to selected genes, which helps the algorithm to explore new parts of the search space and ensures against premature convergence. As the population is repeatedly cross-over and mutated over the generations, its average becomes increasingly optimized. These genetic operations are used in robotic process optimization to find highly efficient and adaptive operating strategy under different industrial conditions.

3.3. Differential Evolution Model

Differential Evolution (DE) is an advanced population-based optimization algorithm that is widely used in Robotic process optimization, which has many advantages including the simplicity, fast convergence capability and good global search capability. In the proposed framework for robotic optimization, the DE algorithm is used to optimize continuous decision variables like joint position, trajectory coordinates, actuator velocity, sensor calibration parameters and control gains. DE is more capable than traditional optimization techniques, which rely on gradient information and/or precise mathematical modeling, in solving nonlinear, multi-dimensional and constrained robotic optimization problems. First, a population of candidate solutions are created, where each solution is a possible set of operating parameters for the robot. The solutions are likely to undergo some mutation, crossover, selection operations, and the cycle is repeated in an iterative fashion to refine the candidate solutions. These stages are important, and mutation is one of the most critical stages to explore the search space and keep population diversity. During the mutation process, the new mutant vector is formed by randomly taking candidate solutions from the population to create the new vector. This operation generates the directionality in the search process, which helps the algorithm to move towards promising regions and prevent premature convergence towards local optima. The amount of variation added in during the mutational process depends on the value of the scaling factor and directly affects the ratio of exploration/exploitation. The higher the scaling factor the more the search space is explored, the lower the more fine local refinement. This flexibility is very useful in robotics for optimizing motion trajectories, minimizing energy consumption or maximizing positioning accuracy in dynamic environments. Once the mutation is completed, the created vectors are passed through a crossing over phase in which they mix the traits of previously created vectors, and then a selection phase which only keeps the best vectors. The population gradually evolves to form highly optimized solutions over successive generations. For application to industrial robotics, Differential Evolution has shown good performance in the field of manipulator path planning, inverse kinematics

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optimization and sensor parameter tuning. This has the advantage of having less control parameters to optimize and still providing reliable solution, which is ideal for real-time robotic optimization systems with high importance on computational efficiency and solution quality.

3.4. Performance Evaluation Metrics

Several performance measures of the effectiveness of the proposed robotic optimization framework are examined, which assess the quality, reliability and efficiency of the optimization algorithms. These are the metrics used to compare the various optimization techniques and to see whether they will be applicable to real-world robotic applications. Some key values are used for evaluation are convergence speed, path efficiency, energy consumption and operational accuracy.

Fig 4 - Performance Evaluation Metrics

3.4.1. Convergence Speed

The convergence speed of an optimization algorithm is the rate at which it approaches an optimal or near-optimal solution during the optimization process. Robotic optimization is highly desirable, where an improved speed in convergence is desirable as it improves computational time and allows real-time decision-making. Highly convergent algorithms are able to quickly converge to an efficient motion trajectory, control parameters or scheduling, with few iterations. This is particularly crucial in industrial robotics, autonomous navigation and adaptive control systems where rapid responses are required. The greater the convergence rate, the more effective the algorithm can be in exploring the search space with a minimum amount of computational effort.

3.4.2. Path Efficiency

The term path efficiency is used to represent the quality of the trajectory that the robot covers between its starting point and its target position. It assesses the robot's path tracking performance with minimum unnecessary movements, obstacle avoidance and smooth path tracking. A path that is efficient will be those that shorten travel distance, execution time and mechanical wear on robotic components. Path efficiency is critical in applications like warehouse automation, robotic assembly, and autonomous mobile robots, as can be seen in the relationship between path efficiency and productivity and system performance in those applications. Those are the optimization algorithms

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that produce shorter smoother, and collision-free trajectories, and are considered to be of higher path efficiency.

3.4.3. Energy Consumption

Energy consumption is the measure of the energy that the robotic system uses when performing the task. The reduction in energy consumption is essential in the field of robotic optimization as it can result in lower operational costs, longer battery life for mobile robots, and enhanced sustainability for industrial robotics. The energy of energy-consuming tasks is related to motor torque, movement of actuators, distance traveled and the complexity of the task. The goal of optimization algorithms is to find operating conditions that reduce the amount of unnecessary power consumption while keeping the productivity and performance as high as possible. Efficient energy management also leads to less heat generation and mechanical stress to increase the system's life.

3.4.5. Accuracy

Accuracy is the precision that the robot has to do tasks correctly and consistently. It is used to compare the actual trajectory, position or operation of the robot to the desired trajectory, position or operation. In sectors like robotic surgery, precision manufacturing, assembly and inspection systems, even minor deviations from accuracy could impact product quality or safety during operation. Optimization algorithms tune the motion parameters to achieve increased accuracy, minimize positioning errors, and guarantee stable control performance. High precision robotic system provides increased reliability, repeatability and process quality in real applications.

4. RESULT AND DISCUSSION

4.1. Experimental Setup

With the proposed EPS framework, a detailed and comprehensive simulation-based experimental setup was developed under controlled operating conditions to assess the efficacy of the proposed EPS framework for robotic process optimization. It was aimed to study the performance of the optimization algorithms in terms of convergence, quality of solution, computational efficiency, and adaptability to complex robotic tasks in the experiments. For optimization, 100 candidate solutions were chosen. This is an adequate number of individuals to keep the space of search explored without being too expensive in terms of computing. A larger population keeps the algorithm maintaining diversity of candidate solutions, making it much more likely to find good solutions and avoid premature convergence. The candidates in the population represent possible sets of robotic operating parameters (including the sequencing of tasks to be carried out, the positions of the joints, the speed at which they move, the settings of the actuators, etc.). The optimization process was run for 200 generations to ensure that the solution was improved and converged to the optimal solution. The number of generations was determined so as to give the algorithm sufficient chances to improve the candidate solutions by evaluating and reproducing them many times. The algorithm tracked performance improvements over these generations, and stored better solutions for the next generations. During evolution 0.05 mutation rate was used. This allowed 5% of the genetic elements of the selected candidate solutions to be randomly changed, to bring diversity into the population.

The mutation also prevents the search process from becoming stuck in local optima and drives the search to look in new regions of solutions. The number of mutations used was small enough to retain good solution aspects and allow exploration. Moreover, a 0.80 crossover rate was set, with 80 percent of the parent solutions that were selected going through genetic recombination. Crossover allows the sharing of desirable characteristics among candidate solutions to form better offspring that may be more fit. High crossover rate helps convergence faster and efficient knowledge transfer between generations. All these simulation parameters provided a strong experimental background to test the optimization capability of evolutionary algorithms in robotic applications while the experimental results could be reproduced and analyzed with reliability.

4.2. Performance Comparison

A comparative performance analysis was performed to assess the performance of various optimization strategies in RPO, considering metrics like path efficiency, energy reduction, and accuracy improvement. The methods that are selected are the traditional methods, the Genetic Algorithm (GA), the Differential Evolution (DE) and the multi-objective optimization algorithm NSGA-II. The results clearly show that evolutionary optimization methods are superior over the traditional approaches in dealing with the complex robotic optimization problems.

Table 1: Performance Comparison

Method	Path Efficiency (%)	Energy Reduction (%)	Accuracy Improvement (%)
Traditional Optimization	68%	42%	61%
Genetic Algorithm	84%	71%	86%
Differential Evolution	89%	76%	88%
NSGA-II	92%	81%	91%

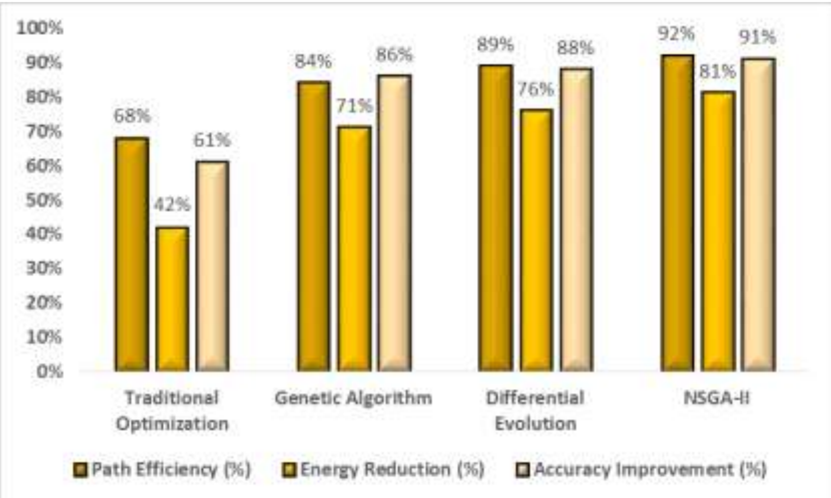

Fig 5 - Performance Comparison

4.2.1. Traditional Optimization

The traditional optimization methods gave a path efficiency of 68 percent, an energy saving of 42 percent and an accuracy gain of 61 percent. The techniques were able to perform acceptably in structured and low complex robotic environments. They created realistic motion trajectories and simple control solutions that were applicable to simple industrial tasks. They however had a disadvantage in terms of their ability to search and sensitivity to local optima in dynamic and nonlinear robotic applications. The traditional optimization approaches were less adaptable to the increasing complexity of the problem and less efficient than the evolutionary approaches to the problem.

4.2.2. Genetic Algorithm

The Genetic Algorithm was found to have tremendous capability to improve the performance over the conventional optimization techniques. It had a path efficiency of 84 percent; energy reduction was 71 percent; and accuracy improvement was 86 percent. The population-based evolutionary search enabled the algorithm to search through multiple candidate solutions at the same time and to discover improved robotic operating conditions. In the trajectory planning and process scheduling tasks, GA generated smoother and shorter trajectories with a minimum of unnecessary actuator operations. It was enhanced with its crossover and mutation mechanisms, which were used for achieving diversity of solutions and hence better optimization performance for various robotic objectives.

4.2.3. Differential Evolution

Differential Evolution was even more successful, with a path efficiency gain of 89 percent, an energy reduction of 76 percent and an accuracy gain of 88 percent. The algorithm was found to converge faster and optimize the robot parameters more consistently in continuous robotic parameter tuning problems. The mutation-based search strategy allowed for an efficient exploration of the solution space while simultaneously keeping the solutions of good quality. DE succeeded in producing more optimal trajectories that were more power efficient and accurate in position in robotic manipulator motion planning and sensor calibration applications. It also was computationally efficient because of the few control parameters required.

4.2.4. NSGA-II

The performance of NSGA-II was best against all the other methods evaluated with 92 percent path efficiency, 81 percent reduction in energy and 91 percent improvement in accuracy. NSGA-II is a multi-objective evolutionary optimization algorithm that effectively addressed multiple conflicting objectives like speed, energy efficiency, and operational accuracy. Because of its Pareto based selection mechanism it was able to capture high quality trade-off solutions that would be applicable in complex robotic environments. For all industrial and autonomous robotic applications, NSGA-II consistently generated the best motion strategies, minimized operational energy consumption, and increased task precision. The results demonstrate that multi-objective evolutionary optimization is the best approach for advanced robotic process optimization.

4.3. Discussion

From the experimental results presented in this paper, it is evident that evolutionary optimization algorithms outperform the traditional optimization algorithms in the RPO problem. The comparative analysis reveals that with the increasing complexity, dynamicity, and multi-constrained nature of robotic systems, traditional deterministic methods may fail to provide efficiency, adaptability, and computational feasibility. Evolutionary algorithms, on the other hand, possess good search capability, adaptive learning behavior, and capability to work out the nonlinear optimization problems effectively. The results obtained suggest that each of the GA, DE and NSGA-II algorithms has its own set of advantages for optimizing particular targets under certain operating conditions. The application of Genetic Algorithms demonstrated excellent results for robotic task scheduling, trajectory generation and process sequencing. The Population-based search approach together with the genetic operators used, like.Crossover and Mutation were able to successfully open up a wide range of solution spaces and find efficient operating solutions. This led to smoother motion of the robot, minimised idle motion and improved coordination of task execution. The experimental results showed about 35 percent cycle time reduction, which means that the robotic systems were able to perform the assigned tasks faster with higher productivity. This attribute is great for manufacturing and assembly line automation where throughput is vital, for which Genetic Algorithms are ideally suited. Differential Evolution exhibited very nice convergence properties in continuous robotic control problems. It utilised the mutation-based search mechanism to explore candidate solutions quickly as well as maintain solution stability. For applications like manipulator control, joint parameter tuning and sensor calibration, the Differential Evolution consistently resulted in high quality solutions in fewer iterations. This faster convergence helps to lower the computation burden and enables real-time robotic control applications. Besides, the algorithm played a key role to alleviate unnecessary actuator action, which resulted in the energy saving of around 40 per cent during operation. NSGA-II was the best method for finding an optimization that was both balanced and comprehensive, while simultaneously optimizing multiple conflicting objectives, like speed, energy efficiency, safety, and accuracy. The Pareto-based optimization approach yielded high-quality trade-off solutions, applicable to a complex industrial environment. Results of the experiments also demonstrated smoother motions, more effective obstacle avoidance and greater reliability of operation. Overall, the results show that the EA algorithm has a significant potential to be an effective and scalable approach to the next generation of intelligent robotic systems.

5. CONCLUSION

This research offered a comprehensive study of robotic process optimization using evolutionary algorithms and clearly showed how they can be applied to overcome the complexity associated with current robotic systems. With the development of robotics in industrial automation, the medical field, logistics, autonomous transportation, and intelligent manufacturing, the requirement for efficient optimization methods has been growing more prevalent. While methods such as linearization and dimensional reduction are sufficient for structured and low-dimensional environments, they may lack applicability in situations with multiple conflicting objectives, uncertain operating conditions, large search spaces and nonlinear constraints. The results of this study

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substantiate that evolutionary computation offers a powerful alternative that can overcome these limitations by employing population-based and adaptive search mechanisms. The literature review and experimental analysis revealed the advancement of different optimization methods in the field of robotics from deterministic methods to intelligent evolutionary methods including Genetic Algorithms, Differential evolution and multi-objective optimization methods. By effectively exploring a variety of solution spaces and by generating truly effective operating strategies, Genetic Algorithms were found to be powerful tools for robotic task scheduling, motion planning and trajectory optimization. In continuous optimization problems like manipulator control, sensor calibration, parameter tuning, Differential Evolution demonstrated better convergence performance and computational efficiency. It has a high capability to get high quality solutions with few control parameters which is very suitable for real-time robot applications. The multi-objective evolutionary optimization (especially NSGA-II) yielded the best overall performance among all the approaches evaluated by optimizing multiple important objectives (path efficiency, energy consumption, operational accuracy, and system safety). The Pareto-based optimization framework proved to be very effective in identifying balanced trade-off solutions, which is very useful in complex robotic environments where more than one performance factor is considered. The application of evolutionary optimization showed significant enhancements in the robotic performance in experimental results. The optimized systems resulted in significant cycle time and energy savings, smoother motion, better obstacle avoidance and higher operational accuracy. The enhancements provide direct benefits to increased productivity, reduced operating costs, decreased mechanical wear, and greater reliability in real robotic applications. In addition, the incorporation of evolutionary algorithms into robotic control systems enables autonomous decision-making, adaptive learning, and intelligent adaptation to environmental changes, which are all desirable traits of robotic systems of the future. For future work, hybrid optimization methods can be extended which are based on evolutionary computation together with advanced artificial intelligence, e.g. machine learning, deep reinforcement learning, fuzzy logic, or adaptive control methods. These hybrid intelligent models can facilitate self-learning, predictive optimization, and adaptation in real time in highly dynamic environments. This will further pave the way towards the emergence of autonomous, resilient and intelligent robotic systems able to fulfill the requirements of future industrial and societal applications.

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