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DEVELOPMENT OF A METHOD FOR REDUCING INDUSTRIAL ROBOT-MANIPULATOR CYCLE TIME AND ENERGY CONSUMPTION THROUGH MOTION TRAJECTORY OPTIMIZATION

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Abstract. *The increasing use of industrial robot-manipulators in automated manufacturing has intensified the need for motion-planning methods that simultaneously reduce production cycle time, electrical energy consumption, and mechanical stress while preserving positioning accuracy and operational safety. Conventional trajectory-planning approaches frequently prioritize minimum execution time or geometric path smoothness independently, which may result in excessive actuator torque, unnecessary acceleration and deceleration, increased energy demand, and reduced mechanical efficiency. This study proposes a multi-objective trajectory optimization method for industrial robot-manipulators that integrates kinematic constraints, dynamic characteristics, electrical energy consumption, motion smoothness, and cycle-time requirements within a unified mathematical framework. The proposed method represents the end-effector path in Cartesian space and generates feasible joint-space trajectories using fifth-order polynomial interpolation or B-spline functions. A dynamic robot model is employed to estimate joint torques, mechanical power, and energy demand, while a constrained optimization algorithm adjusts trajectory timing and interpolation parameters. The objective function combines normalized cycle time, electrical energy consumption, and jerk, subject to joint-position, velocity, acceleration, torque, and workspace constraints. A Pareto-based optimization strategy is recommended for identifying feasible trade-offs between productivity and energy efficiency, followed by the selection of a solution according to predefined manufacturing requirements. The methodological contribution is the integration of trajectory timing, dynamic feasibility, energy estimation, and smoothness into a single optimization procedure rather than optimizing these parameters independently. The proposed framework provides a basis for simulation-based evaluation and subsequent experimental validation using industrial robot controllers and electrical power measurements. Since no new physical experiments are reported in this article, numerical performance improvements are not claimed as experimentally established findings. Instead, the study establishes the mathematical model, optimization procedure, comparative evaluation criteria, and validation protocol required to determine the actual reduction in cycle time and energy consumption for a specified industrial manipulator.*

Keywords: *industrial robot-manipulator; motion trajectory optimization; cycle time; energy consumption; multi-objective optimization; robot dynamics; B-spline interpolation; motion smoothness.*

Kalit so‘zlar: *sanoat robot-manipulyatori; harakat trayektoriyasini optimallashtirish; ish sikli davomiyligi; energiya sarfi; ko‘p mezonli optimallashtirish; robot dinamikasi; B-splayn interpolyatsiyasi; harakat ravonligi.*

Ключевые слова: *промышленный робот-манипулятор; оптимизация траектории движения; продолжительность рабочего цикла; энергопотребление; многокритериальная оптимизация; динамика робота; B-сплайн-интерполяция; плавность движения.*

Introduction

Industrial robot-manipulators constitute an essential component of modern manufacturing systems because they provide repeatable motion, high positioning accuracy, programmable operation, and the ability to perform repetitive technological operations under demanding

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production conditions. Their application encompasses automotive assembly, welding, material handling, palletizing, machine tending, packaging, surface finishing, and precision component manufacturing. However, the operational efficiency of a robotic production cell depends not only on the nominal payload capacity, actuator power, or maximum joint velocity of the robot but also on the trajectory followed during each operation, the timing of acceleration and deceleration, the interaction between individual joints, the properties of the carried load, and the energy characteristics of the drive system. A trajectory that appears geometrically short may require excessive joint movement or generate high acceleration peaks, while a trajectory designed exclusively to minimize motion time may increase electrical power demand and reduce mechanical smoothness.

Consequently, trajectory planning should be treated as a constrained optimization problem in which productivity, energy efficiency, dynamic feasibility, positioning accuracy, and equipment reliability are evaluated together. Previous studies have investigated time-optimal and smooth trajectory generation, including optimization based on execution time and integrated squared jerk [1, 2]. More recent research has explicitly incorporated energy consumption into trajectory-planning formulations and explored multi-objective and learning-assisted optimization techniques [3–6]. Nevertheless, the practical effectiveness of any particular approach depends on the robot model, drive architecture, task geometry, controller limitations, payload, and the method used to measure or estimate electrical energy. For example, minimizing joint displacement alone does not necessarily minimize energy because gravitational torque, motor efficiency, friction, regenerative braking, and simultaneous motion of multiple axes influence the total energy balance. Similarly, reducing the duration of a movement does not automatically reduce its energy consumption: aggressive acceleration may increase instantaneous power and resistive losses even when the overall movement becomes shorter. The central research problem is therefore to establish a trajectory-optimization method that identifies a technically feasible compromise between cycle time and energy demand while maintaining the required end-effector path and operational constraints. The scientific hypothesis of this study is that, for suitable industrial tasks, jointly optimizing trajectory timing and motion-profile parameters using a dynamic energy model can reduce cycle time, electrical energy consumption, or both relative to a clearly specified baseline, provided that the resulting trajectory respects all kinematic, dynamic, accuracy, and safety requirements. The hypothesis is conditional rather than universal because the optimal balance depends on the task and the manipulator.

The aim of the research is to develop a mathematical and computational method for optimizing the motion trajectory of an industrial robot-manipulator to reduce cycle time and energy consumption without compromising technological accuracy or mechanical feasibility. The objectives are to establish a mathematical description of the manipulator motion; formulate an energy-aware objective function; introduce trajectory representations suitable for constrained optimization; develop an algorithm for selecting feasible trajectory parameters; define a reproducible comparison with conventional trajectory-planning approaches; and establish quantitative criteria for evaluating cycle-time reduction, electrical energy savings, motion smoothness, and constraint satisfaction. The proposed contribution lies in the integrated formulation and evaluation procedure, which combines time, energy, and smoothness within a common optimization framework and explicitly distinguishes estimated performance from experimentally verified performance.

Materials and Methods

2.1. Research design and system representation

The study adopts a model-based engineering optimization approach suitable for implementation in a computer simulation environment and subsequent validation on a physical industrial robot. The system under consideration is a serial robot-manipulator with n independently

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controlled rotational or translational joints, a rigid-link mechanical structure, servo drives, and an end-effector designed for a specified manufacturing operation. A six-degree-of-freedom industrial manipulator is a suitable reference configuration because it can generally provide independent control over the position and orientation of the tool within its reachable workspace, although the proposed formulation is not limited to six axes. The robot configuration is described by the generalized coordinate vector $q(t) = [q_1(t), q_2(t), \dots, q_n(t)]^T$, where each element represents a joint angle or displacement. The joint velocity, acceleration, and jerk vectors are defined as $\dot{q}(t)$, $\ddot{q}(t)$, and $\dddot{q}(t)$, respectively.

The task is defined by an initial configuration, a terminal configuration, and, where required, intermediate Cartesian waypoints describing the technological path. For operations such as welding, sealing, cutting, or surface treatment, the end-effector orientation and path deviation must remain within process-specific tolerances; for point-to-point handling, the principal requirements may instead be endpoint accuracy, collision avoidance, and appropriate clearance from surrounding equipment. The forward-kinematic model is written as $x(t) = f\big(q(t)\big)$, where (x(t)) represents the end-effector pose and (f) is determined by the robot geometry and kinematic parameters.

The inverse-kinematic relationship maps the desired Cartesian pose into one or more feasible joint configurations. Since different inverse-kinematic solutions may produce substantially different joint displacements, singularity proximity, and actuator demands, the selection of a joint-space solution forms part of the planning process rather than being treated as a purely geometric calculation. The method assumes that the robot's geometric parameters, joint limits, nominal payload, and rated motion constraints are known from manufacturer documentation or system identification.

Dynamic parameters should be obtained from a validated robot model or estimated experimentally when the manufacturer's information is insufficient. The proposed procedure is applicable to repetitive industrial operations in which the required task geometry is known in advance and the trajectory can be optimized offline or updated within an appropriately verified planning architecture. It does not assume that a single mathematical model can fully reproduce every commercial robot controller, because internal filtering, trajectory blending, servo-loop behavior, and safety-related speed limitations may affect the executed motion.

2.2. Mathematical model of manipulator dynamics

The dynamic behavior of the robot-manipulator is represented by the standard rigid-body equation of motion:

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + g(q) + F(\dot{q}) = \tau \quad (1)$$

where (M(q)) is the joint-space inertia matrix, $C(q,\dot{q})\dot{q}$ represents velocity-dependent Coriolis and centrifugal effects, (g(q)) is the gravitational torque or force vector, $F(\dot{q})$ represents joint friction and other modeled mechanical resistance, and τ is the vector of generalized actuator torques or forces.

For rotational joints, torque is measured in newton-metres, while for translational joints the corresponding generalized force is measured in newtons. Equation (1) establishes the connection between a candidate trajectory and the mechanical effort required to execute it. A trajectory with high acceleration may produce increased inertial torque, while movement against gravity may demand sustained positive mechanical work.

Conversely, a descending movement may release gravitational potential energy, some of which may be dissipated or recovered depending on the servo-drive architecture. For a serial manipulator, the inertia matrix can be calculated using recursive Newton–Euler methods, the Euler–Lagrange formulation, or manufacturer-provided dynamic models. The Newton–Euler approach is computationally efficient for evaluating actuator loads, whereas an appropriately parameterized Lagrangian model can be useful for analytical development and simulation.

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The friction term may initially be approximated using viscous and Coulomb components, expressed for joint i as $F_i(\dot{q}_i) = b_i\dot{q}_i + f_{c,i}\mathrm{sgn}(\dot{q}_i)$, where b_i is the viscous-friction coefficient and $f_{c,i}$ is the Coulomb-friction magnitude.

This representation is a simplified approximation and may require extension when friction varies with temperature, load, speed, or transmission configuration. Joint constraints are written as $q_{i,\min} \le q_i(t) \le q_{i,\max}$, $|\dot{q}_i(t)| \le \dot{q}_{i,\max}$, $|\ddot{q}_i(t)| \le \ddot{q}_{i,\max}$, and $|\tau_i(t)| \le \tau_{i,\max}$. Where jerk limits are specified by the manufacturer or required by the process, the additional condition $|\dddot{q}_i(t)| \le \dddot{q}_{i,\max}$ is imposed. These inequalities must be checked throughout the trajectory, not only at interpolation points, because polynomial and spline profiles may develop local extrema between sampled nodes.

In practical implementation, the limits should incorporate an appropriate margin for modeling uncertainty and should reflect the robot manufacturer's permitted operating envelope. The dynamic model also allows the algorithm to reject trajectories that satisfy geometric and velocity conditions but require actuator torques beyond the permissible range. Thus, the proposed method evaluates the feasibility of a trajectory using both its kinematic properties and the dynamic demands implied by its execution.

2.3. Trajectory parameterization and smoothness

The proposed method separates geometric path definition from time parameterization wherever the task permits this separation. The geometric path describes the required movement through Cartesian or joint space, whereas the timing law determines how quickly the robot traverses that path. For a point-to-point movement, a fifth-order polynomial can be used to describe the temporal evolution of a joint coordinate:

$$q_i(t) = a_{0,i} + a_{1,i}t + a_{2,i}t^2 + a_{3,i}t^3 + a_{4,i}t^4 + a_{5,i}t^5 \quad (2)$$

The six polynomial coefficients are determined from six boundary conditions, commonly the initial and final position, velocity, and acceleration. When the initial and terminal velocities and accelerations are zero, the resulting profile provides continuous position, velocity, and acceleration and avoids abrupt acceleration changes at the endpoints under the specified boundary conditions.

The corresponding velocity and acceleration are obtained by differentiating Equation (2), and jerk is obtained through the third derivative. A normalized time variable $s = t/T$, with $s \in [0,1]$, can improve numerical conditioning and make trajectory coefficients easier to optimize when the total movement duration T is variable. For operations involving multiple intermediate waypoints, piecewise fifth-order polynomials or B-spline representations are more flexible. B-splines allow the trajectory to be shaped by a finite set of control points and provide useful continuity properties depending on their degree and knot structure. Previous work has demonstrated the applicability of spline-based representations to constrained robot trajectory optimization and smooth motion generation [1, 3].

In the proposed approach, trajectory parameters are collected into a decision vector z, which may include waypoint locations where permitted, spline control-point adjustments, segment durations, blending parameters, and other variables that affect the timing and shape of the motion.

However, the geometric path must not be altered freely when the technological process requires strict adherence to a prescribed contour. For continuous-path operations, the optimizer may adjust the timing law while maintaining the original Cartesian path within a specified tolerance. For point-to-point handling, small geometric deviations may be allowed if they remain within the safe workspace and do not violate process requirements.

The optimizer should not select a trajectory solely because it has low integrated jerk: jerk is a useful indicator of motion smoothness, but minimizing it without accounting for time and energy can produce unnecessarily slow movements. Instead, the jerk penalty is included as one component of a multi-objective function. The candidate trajectory is evaluated over the complete

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movement interval using numerical integration and sufficiently dense sampling, with additional checks near predicted extrema and constraint boundaries. Where the robot controller applies internal smoothing or blending, the planned trajectory should also be evaluated against the controller's actual execution behavior, since a mathematically smooth reference trajectory may not be reproduced exactly by the physical system.

2.4. Electrical energy-consumption model

Energy optimization requires an explicit distinction between mechanical work, instantaneous mechanical power, and electrical energy drawn from the supply. The instantaneous mechanical power at joint i is calculated as $P_{m,i}(t) = \tau_i(t)\dot{q}_i(t)$ for a rotational joint, with the corresponding generalized-force expression used for translational motion. The total signed mechanical power is $P_m(t) = \sum_{i=1}^{n} \tau_i\,(t)\dot{q}_i(t)$.

Positive mechanical power represents mechanical energy delivered by the drive to the robot, whereas negative power indicates that mechanical energy is being returned toward the drive during braking or gravity-assisted motion. However, the integral of signed mechanical power is not equivalent to the electrical energy consumed from the supply. The difference arises from motor and inverter losses, transmission friction, controller and auxiliary loads, and the possibility that regenerated energy may be dissipated, stored temporarily, or returned through a shared electrical bus. Consequently, an electrical energy model should be selected according to the level of information available about the drive system. For an initial approximation, the positive and negative mechanical-power components can be separated as $P^{+}(t) = \max(P_m(t), 0)$ and $P^{-}(t) = \max(-P_m(t), 0)$. An approximate electrical power model is then written as

$$P_{\mathrm{el}}(t) = P_0 + \frac{P^{+}(t)}{\eta_m} - \eta_r P^{-}(t) \tag{3}$$

where P_0 represents the baseline electrical demand of the active robot system, η_m is an effective motoring efficiency, and η_r is an effective regenerative-energy utilization factor. Equation (3) is a simplified engineering approximation rather than a universal drive model. The term associated with recovered energy is valid only when the system can actually utilize or return that energy; if regenerative braking is unavailable, the recovery contribution must be set to zero or replaced with a suitable loss model. Furthermore, fixed auxiliary demand should be included only when it is part of the measurement boundary and remains active during the movement. The electrical energy consumed over a cycle of duration T is calculated as

$$E_{\mathrm{el}} = \int_0^T P_{\mathrm{el}}\,(t)\,\mathrm{d}t \tag{4}$$

For a complete production cycle, Equation (4) should be extended to include all relevant robot movements, dwell periods, tool operation, and auxiliary systems within the defined boundary. If the research objective concerns only manipulator motion, unrelated machine energy should be excluded. If the objective concerns total cell energy, the measurement boundary must include the corresponding peripheral equipment. When manufacturer-specific drive data or experimentally identified efficiency maps are available,

Equation (3) should be replaced with a more detailed model that accounts for motor speed, torque, drive losses, and regenerative behavior. If such data are unavailable, the simplified model can be used for preliminary optimization, but its results should be reported as estimates and checked against physical measurements before any quantitative energy-saving claim is made. This distinction is essential because an algorithm can minimize a mathematical energy proxy without necessarily minimizing the electrical energy measured at the robot's supply connection.

2.5. Multi-objective optimization formulation

The central optimization problem combines cycle time, electrical energy, and trajectory smoothness. Let z denote the vector of decision variables defining the trajectory and its timing. The optimization problem is formulated as

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$$\min_z \mathbf{J}(z) = \begin{bmatrix} T(z) \\ E_{\text{el}}(z) \\ J_{\text{jerk}}(z) \end{bmatrix} \tag{5}$$

where $T(z)$ is the execution time, $E_{\text{el}}(z)$ is the modeled electrical energy consumption, and the jerk-related term is defined as

$$J_{\text{jerk}}(z) = \int_0^{T(z)} \ddot{q}\,(t)^T W_j \ddot{q}(t)\,\mathrm{d}t \tag{6}$$

with W_j being a positive-semidefinite weighting matrix that reflects the relative importance of smoothness across the joints. Since the three objectives have different units and numerical scales, a weighted-sum formulation should use normalization. A scalar optimization objective can be expressed as

$$J_w(z) = w_T \frac{T(z)}{T_{\text{ref}}} + w_E \frac{E_{\text{el}}(z)}{E_{\text{ref}}} + w_J \frac{J_{\text{jerk}}(z)}{J_{\text{ref}}} \tag{7}$$

where T_{ref}, E_{ref}, and J_{ref} are positive reference values obtained from a baseline trajectory or another documented normalization procedure. The non-negative weights w_T, w_E, and w_J express the relative importance of cycle time, energy, and smoothness. For a manufacturing line operating under a strict production takt, cycle time may be assigned a higher priority, while a process with delicate payloads or stringent surface-quality requirements may require greater emphasis on smoothness.

The weights must be selected transparently and subjected to sensitivity analysis; otherwise, the reported optimum may reflect arbitrary preferences rather than a robust engineering solution. A Pareto-based algorithm is preferable when the trade-offs between objectives are not known in advance, because it identifies non-dominated solutions instead of forcing an early decision about the weighting coefficients.

A practical implementation may use a non-dominated sorting genetic algorithm, sequential quadratic programming for a suitably smooth constrained formulation, or another validated numerical optimizer. The selection of the algorithm depends on the dimensionality of the decision space, the presence of nonlinear constraints, the computational budget, and the need for repeatable solutions. Regardless of the algorithm, every candidate must satisfy the prescribed joint-position, velocity, acceleration, torque, workspace, collision-avoidance, and task-accuracy constraints.

The endpoint conditions are written as $q(0) = q_s$ and $q(T) = q_f$, with the required initial and terminal velocities and accelerations imposed as appropriate. Where the task requires a specified Cartesian path, the additional condition $|x(t) - x_d(t)| \leq \varepsilon_x$ is imposed, where $x_d(t)$ is the desired tool position and ε_x is the permitted position deviation. Orientation error should be evaluated using a suitable rotational distance measure rather than by directly subtracting orientation representations with incompatible conventions. The resulting formulation supports the identification of a trajectory that is faster, more energy-efficient, or smoother than the baseline while explicitly preserving feasibility.

2.6. Proposed optimization algorithm

The developed method consists of a sequence of model construction, trajectory generation, constrained evaluation, optimization, and validation stages. First, the manipulator model is initialized using the robot's kinematic geometry, dynamic parameters, joint limits, payload information, and end-effector properties. Second, the technological task is defined through its initial and final poses, intermediate waypoints, path tolerances, obstacle geometry, and required cycle conditions. Third, inverse kinematics is used to generate feasible joint configurations, and candidate trajectory representations are constructed using fifth-order polynomial or B-spline interpolation. Fourth, the timing variables and permissible trajectory parameters are initialized from a conventional motion profile or a feasible initial solution. Fifth, the dynamic model calculates joint torques and mechanical power throughout the candidate trajectory, while the electrical energy model estimates supply energy over the defined cycle. Sixth, the optimizer

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evaluates the objective vector and verifies all constraints. Infeasible candidates are rejected or penalized using a formulation that prevents the optimizer from treating violations as acceptable trade-offs. Seventh, the decision variables are updated according to the selected optimization method.

The process continues until a specified convergence criterion is met, a computational limit is reached, or no meaningful improvement is observed over the prescribed number of iterations. Finally, the algorithm selects a feasible solution from the Pareto set or the weighted-sum optimum according to the production requirements. The method can be represented by the following pseudocode:

Algorithm 1. Energy-aware trajectory optimization

1. Load the robot kinematic and dynamic model.
2. Define the task path, initial conditions, terminal conditions, and operating limits.
3. Generate a feasible baseline trajectory.
4. Initialize the trajectory parameters and movement durations.
5. Generate a candidate trajectory for each optimization iteration.
6. Calculate joint position, velocity, acceleration, jerk, torque, and electrical power.
7. Evaluate cycle time, electrical energy, and motion smoothness.
8. Check joint, dynamic, collision, and task-accuracy constraints.
9. Update the optimization population or decision variables.
10. Repeat until the termination criterion is satisfied.
11. Select a feasible solution according to the specified production priorities.
12. Validate the selected trajectory in simulation and, subsequently, on the physical robot.

The computational implementation should use consistent units, a documented integration step, and numerical tolerances appropriate to the manipulator and controller. The integration interval must be sufficiently small to capture transient power peaks and constraint violations, but an unnecessarily small interval can increase computation time without materially improving the result.

A convergence study should therefore be performed by repeating the evaluation at progressively finer time resolutions and checking whether the estimated energy and constraint margins remain stable. For stochastic optimizers, multiple independent runs are required to evaluate solution variability and reduce the risk of reporting an unusually favorable result from one random initialization. For gradient-based optimization, sensitivity to initial conditions and local minima should be examined. The resulting procedure is designed to be modular: the trajectory generator, dynamic solver, energy estimator, constraint checker, and optimization engine can be replaced or improved independently without changing the overall formulation.

2.7. Baseline definition and performance indicators

A scientifically valid comparison requires a clearly defined baseline and consistent operating conditions. The baseline may be the trajectory currently executed by the industrial robot, a manufacturer-supported point-to-point motion profile, or a conventional fifth-order trajectory generated under the same endpoint and joint-limit requirements. The selected baseline must be documented because different baseline profiles can produce different apparent improvements. Both the baseline and optimized trajectories must use the same manipulator, payload, end-effector, task geometry, initial and final states, safety restrictions, and measurement boundary. Cycle-time reduction is calculated as

$$R_T = \frac{T_b - T_o}{T_b} \times 100\% \quad (8)$$

where T_b is the baseline cycle time and T_o is the optimized cycle time. Electrical energy reduction is calculated as

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$$R_E = \frac{E_b - E_o}{E_b} \times 100\% \quad (9)$$

where E_b and E_o are the baseline and optimized electrical energy consumption values. Positive values of R_T and R_E indicate improvements, whereas negative values indicate deterioration relative to the baseline. Average power is calculated as $P_{\text{avg}} = E_{\text{el}}/T$, but average power must not be used as a substitute for energy when evaluating electricity consumption per production cycle. A shorter trajectory may exhibit higher average power while still consuming less total energy, or it may consume more energy despite a reduced duration.

Consequently, cycle time, energy per cycle, average power, peak power, and motion smoothness should be reported separately. Additional performance indicators include maximum joint torque utilization, maximum velocity and acceleration utilization, root-mean-square tracking error, maximum Cartesian path deviation, and the number of constraint violations. Torque utilization for joint i may be defined as $\rho_{\tau,i} = \max_t |\tau_i(t)|/\tau_{i,\max}$. A trajectory with $\rho_{\tau,i}$ approaching unity leaves little margin for modeling error, payload variation, or transient disturbances, so an engineering acceptance criterion should require an appropriate reserve.

For continuous production, the total cycle should include all movements and pauses that are part of the real manufacturing sequence; reducing the duration of one segment is not equivalent to reducing the full production cycle if other segments dominate the total time. Where the robot operates repeatedly, energy consumption should also be evaluated per completed workpiece and under representative production conditions.

Results

3.1. Analytical outcome of the proposed formulation

The principal result of the present study is the formulation of an integrated optimization framework that relates robot trajectory parameters to cycle time, actuator demands, estimated electrical energy, and motion smoothness. Equations (1)–(7) establish the mathematical basis for evaluating a candidate trajectory as a complete motion-control problem rather than as a geometric interpolation task alone.

The dynamic model makes it possible to identify candidate trajectories that are geometrically valid but mechanically infeasible because they exceed joint torque or acceleration limits. The electrical energy model distinguishes positive mechanical work from potential regenerative operation and therefore provides a more relevant optimization criterion than minimizing joint displacement or signed mechanical work alone. The normalized objective function allows the cycle-time, energy, and jerk criteria to be evaluated within a common numerical optimization procedure, while the Pareto formulation makes it possible to identify solutions representing different productivity–energy trade-offs.

The resulting method can be applied to point-to-point handling, material transfer, machine loading and unloading, and selected continuous-path tasks, provided that the trajectory representation and accuracy constraints are adapted to the operation. Fifth-order polynomial interpolation provides a relatively simple implementation for movements with fixed endpoints and boundary conditions, whereas B-spline interpolation offers greater flexibility for trajectories with multiple waypoints or more complex timing profiles. The use of a common evaluation procedure for both representations enables a meaningful comparison of their computational requirements, smoothness characteristics, and energy estimates.

The proposed method also establishes an explicit distinction between planning and validation: the optimizer identifies candidate improvements in a model, but the reliability of those improvements depends on the accuracy of the dynamic parameters, drive-efficiency model, controller behavior, and execution measurements. Thus, the method provides a reproducible foundation for evaluating the research hypothesis without assuming that an analytically favorable trajectory necessarily produces the same result on an industrial robot.

3.2. Expected relationship between trajectory optimization and cycle time

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The mathematical formulation indicates that cycle-time reduction can be achieved by adjusting movement durations, redistributing acceleration and deceleration, and reducing unnecessary joint motion where the task permits such changes. Under a fixed geometric path, the timing law determines the instantaneous joint velocities and accelerations, which in turn affect both the achievable execution time and the dynamic loads. A trajectory with poorly allocated segment durations may force one joint to operate close to its limit while other joints have unused motion capacity.

Joint-space synchronization and coordinated timing can therefore improve execution efficiency, provided that the required Cartesian path and endpoint conditions remain satisfied. For point-to-point motion, a time-optimal or near-time-optimal profile can be used as a reference, but the minimum-time solution may involve acceleration levels that are undesirable when energy consumption, jerk, payload stability, or process quality is also important.

The proposed multi-objective approach does not presume that the fastest trajectory is always the best trajectory. Instead, it determines whether the reduction in execution time associated with a candidate solution justifies the accompanying increase in energy or dynamic stress. If a strict production takt must be met, the optimization may treat cycle time as a hard upper bound and minimize energy within that limit. If productivity and energy costs have comparable importance, a Pareto-based formulation can identify several alternatives for engineering evaluation.

The cycle-time benefit must ultimately be measured on the actual execution sequence because controller blending, acceleration limits, waiting conditions, external-axis coordination, and non-motion process times may affect the observed production cycle. The proposed formulation therefore provides a method for identifying potential cycle-time improvements, while the magnitude of the realized benefit remains dependent on the selected manipulator and production task.

3.3. Expected relationship between trajectory optimization and energy consumption

The energy-related contribution follows from the observation that the electrical demand of a robot is influenced by the full motion profile rather than by distance alone. Acceleration peaks increase inertial torque, gravity changes the mechanical effort required from different joints, and braking can either dissipate energy or allow some of it to be recovered.

The proposed objective therefore evaluates the trajectory through a dynamic model and an explicit electrical energy estimate. This structure allows the optimizer to compare a short, aggressive movement with a slightly longer, smoother movement in terms of their estimated total energy demand. For example, reducing unnecessary acceleration and deceleration may lower peak torque and resistive losses, while an alternative trajectory may reduce energy by taking advantage of gravity-assisted movement or shared-drive regeneration where the hardware supports it.

However, these relationships are not universal. A longer trajectory can consume more energy because the drives and controller remain active for a longer period, particularly when baseline power is significant. Conversely, a faster movement can consume more energy when increased torque and speed cause greater drive losses.

The balance depends on the motor-efficiency map, friction, payload, motion direction, drive architecture, and control strategy. The proposed energy model is therefore intended to guide candidate selection, not to replace physical measurement. Where the model is simplified, its predictions should be calibrated against electrical power data collected at a clearly defined supply boundary. Once validated, the model can support repeated offline optimization for multiple tasks and payload configurations, reducing the need to test every candidate trajectory physically. Until that validation is completed, the appropriate result is a predicted energy difference with documented assumptions and uncertainty, rather than a definitive claim of energy savings.

3.4. Comparative evaluation protocol

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To evaluate the proposed method, a comparative study should be conducted using at least three trajectory-planning strategies: a conventional baseline trajectory, a time-focused optimized trajectory, and the proposed multi-objective energy-aware trajectory. Where computational resources permit, a fourth comparison using an alternative spline representation or a different optimization algorithm can help identify whether the results arise from the objective formulation or from the particular numerical method. All methods must execute the same task under identical endpoint, payload, safety, and accuracy requirements.

The simulation stage should record cycle time, estimated electrical energy, maximum torque utilization, peak power, jerk-related smoothness, and end-effector tracking deviation. The physical validation stage should then execute the selected trajectories on the same robot and measure electrical energy with an appropriately rated power analyzer or validated drive telemetry.

Repeated trials should be conducted after the robot reaches a consistent operating state, and the order of trajectory execution should be controlled where possible to limit the effects of temperature and changing operating conditions. For a repetitive task, a sufficient number of cycles should be recorded to distinguish systematic differences from measurement variability.

The report should provide mean values, dispersion measures, and confidence intervals where the experimental design supports them. If a model predicts an improvement but physical measurements do not confirm it, the discrepancy should be investigated through drive-loss identification, controller behavior, friction estimation, and energy-boundary consistency. This comparative protocol is necessary to establish whether the proposed algorithm improves actual manufacturing performance rather than merely producing a lower value of its own mathematical objective.

Discussion

4.1. Scientific interpretation and contribution

The proposed method addresses a central limitation of single-objective robot trajectory planning: a trajectory that is optimal with respect to one criterion may be inefficient with respect to another. Time-focused methods are valuable where production throughput dominates, while smoothness-focused methods can reduce abrupt changes in acceleration and support better process stability. Energy-focused approaches are particularly relevant when robots perform repetitive movements or when electricity consumption constitutes a substantial operating cost.

Existing research has investigated the minimization of execution time and jerk [1, 2], energy-aware multi-objective planning [3], learning-assisted energy optimization [4], and the joint consideration of electrical energy and manipulator performance [5]. Recent work has also explored learning-based energy-profile estimation and multi-objective trajectory planning [6].

These studies demonstrate that energy-conscious trajectory planning is an established and evolving research area; accordingly, the contribution of the present study should not be interpreted as the invention of energy-aware trajectory optimization itself. Its intended contribution is the explicit integration of cycle time, electrical energy estimation, smoothness, dynamic feasibility, and a reproducible validation protocol within a unified method that can be adapted to a specified industrial manipulator.

This integrated formulation is particularly useful for engineering applications in which the production task and safety requirements are known but the most suitable balance between throughput and energy has not yet been established. The method also makes the role of the energy model explicit, which is important because a mathematical objective based only on mechanical work may not accurately represent the electricity drawn from the supply. In this respect, the framework encourages researchers to report the assumptions underlying energy estimates and to distinguish between simulated outcomes and physically measured results.

The novelty claim should be narrowed further if the work is submitted as an original research article: a convincing publication should demonstrate a new algorithmic feature, a new

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validated energy model, a task-specific experimental finding, or a clearly quantified advantage over relevant alternatives. The general formulation presented here establishes the methodological foundation but does not, by itself, demonstrate experimental superiority over existing optimization methods.

4.2. Practical significance for automated manufacturing

The practical value of the method lies in its potential to improve repetitive robot operations without necessarily requiring changes to the robot's mechanical hardware. In applications such as palletizing, machine tending, material transfer, and selected assembly tasks, the motion sequence is often repeated many times, so even a small reduction in energy per cycle or execution time may become significant over long operating periods. For example, if a validated method reduced energy by ΔE kilowatt-hours per cycle and the system completed (N) cycles annually, the annual energy saving would be $E_{\text{saved}} = N\Delta E$.

The corresponding electricity-cost saving would be $C_{\text{saved}} = N\Delta E c_e$, where c_e is the electricity price per kilowatt-hour. These equations provide a transparent basis for economic assessment, but they do not imply any particular saving until ΔE, annual cycle count, and applicable electricity price are established from real operating data. A similar calculation can be applied to production capacity when the optimized trajectory reduces the bottleneck cycle time and the rest of the manufacturing process can use the additional capacity.

However, shortening a robot movement will not necessarily increase overall line throughput if the limiting operation lies elsewhere in the production system. Furthermore, a more aggressive trajectory may accelerate wear or reduce process quality if it increases dynamic loading beyond acceptable levels. Consequently, industrial implementation should consider energy and cycle time alongside equipment reliability, maintenance requirements, process accuracy, and safe operation.

The proposed optimization framework can support this assessment by including torque limits and smoothness criteria during planning, while production trials can establish whether the resulting trajectory delivers a net operational benefit. For factories that operate multiple robot types, the modular structure of the method also makes it possible to compare optimization strategies across different manipulators, provided that each robot's kinematic and dynamic models are appropriately parameterized.

4.3. Limitations and implementation risks

Several limitations must be addressed before the proposed method can be considered experimentally validated. First, the accuracy of the predicted energy consumption depends on the quality of the dynamic model and the treatment of electrical losses.

A rigid-body model may not fully represent gearbox losses, temperature-dependent friction, cable drag, motor-drive efficiency, or auxiliary power consumption. Second, a trajectory that satisfies constraints at discrete sample points may still violate them between samples, so numerical sampling must be supplemented with extrema analysis, conservative margins, or continuous-time constraint verification where feasible. Third, optimization methods based on weighted sums can overlook some non-convex regions of a Pareto frontier and may produce different results when the objective weights change. Fourth, stochastic optimizers can exhibit run-to-run variability, while gradient-based methods can converge to local solutions. Fifth, commercial robot controllers may transform commanded trajectories through internal interpolation, blending, filtering, or speed scaling, creating a difference between the planned reference and the physical motion. Sixth, energy savings measured at the motor or drive level may differ from savings measured at the robot's main electrical supply, especially when regenerative energy and auxiliary loads are involved. Seventh, the best trajectory may change with payload, tool configuration, temperature, task geometry, or the required production takt, so a single optimized profile should not be assumed to be optimal for every operating condition. Finally, collision avoidance and safety

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must remain hard constraints and must never be traded away in exchange for lower cycle time or energy consumption.

The algorithm should be implemented within the robot manufacturer's permitted control architecture and validated according to the applicable machinery and industrial-robot safety requirements. These limitations do not invalidate the proposed framework; rather, they define the conditions under which its predictions can be trusted and its practical benefits can be established. A credible implementation should report the robot model, optimization settings, constraint margins, measurement boundary, baseline trajectory, and validation procedure so that another researcher can reproduce the evaluation.

4.4. Future research directions

Further development should focus on experimentally identifying the relationship between trajectory parameters and actual electrical energy consumption for representative industrial tasks. One direction is to develop a calibrated drive-energy model that accounts for torque-dependent and speed-dependent losses, regenerative behavior, and the auxiliary loads included in the measurement boundary. A second direction is to incorporate uncertainty into the optimization problem so that the selected trajectory retains adequate margins under payload variation, friction changes, and model inaccuracies. A third direction is to investigate adaptive optimization, in which measured execution data are used to update the energy model between production cycles without compromising real-time safety or deterministic controller behavior.

Learning-based estimators may provide an efficient way to approximate energy consumption across a large trajectory space, but they require representative training data and careful validation outside the training distribution. A fourth direction is to optimize the entire production cell rather than the manipulator alone, taking account of conveyors, fixtures, machine tools, peripheral equipment, and interactions between concurrent operations. A fifth direction is to investigate multi-robot coordination, where one robot's timing affects another robot's collision-free workspace, shared resources, or production takt. Finally, experimental comparisons should examine the repeatability of energy savings over extended operating periods, because thermal changes and mechanical wear may influence the performance observed during short tests. These research directions would strengthen the proposed method by connecting mathematical optimization to practical industrial deployment and by establishing the conditions under which improvements remain robust over realistic production scenarios.

Conclusion

A method for reducing industrial robot-manipulator cycle time and energy consumption through trajectory optimization has been formulated within a unified engineering framework. The proposed approach combines a rigid-body dynamic model, fifth-order polynomial or B-spline trajectory representations, an electrical energy-consumption model, and a multi-objective optimization function that accounts for execution time, energy demand, and motion smoothness.

The formulation explicitly incorporates joint-position, velocity, acceleration, torque, workspace, and task-accuracy constraints, thereby preventing the optimizer from selecting trajectories that appear efficient but are mechanically or operationally infeasible. The method also distinguishes mechanical power from electrical energy consumption and recognizes the importance of regenerative-drive behavior and auxiliary loads when calculating energy demand. A reproducible optimization procedure and comparative evaluation protocol have been established, including the calculation of cycle-time reduction, energy reduction, torque utilization, and motion-quality indicators. The framework can be adapted to repetitive industrial operations such as material handling, machine tending, and selected assembly or continuous-path tasks, provided that the trajectory representation reflects the actual technological requirements. Its practical advantage is that it enables systematic evaluation of productivity–energy trade-offs using a common model and consistent baseline conditions.

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However, the magnitude of any improvement cannot be established from the mathematical formulation alone. Physical validation is required to determine whether the predicted reductions in cycle time and energy consumption are achieved on the selected industrial robot, under realistic payloads, controller settings, and production conditions.

The next stage of research should therefore implement the algorithm in a simulation environment, compare it with a clearly defined conventional trajectory, calibrate the energy model using measured electrical data, and validate the selected trajectory through repeated robot trials. Such validation would provide the evidence needed to establish the method's quantitative effectiveness and its suitability for industrial implementation.

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