

Energy-Conscious Trajectory Methods for Robotic Manipulators: A Systematic Review

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ABSTRACT

The growing demand for energy-efficient robotic systems has driven research on energy-conscious trajectory planning and control for manipulators, yet findings remain scattered across methods and evaluation schemes. This systematic literature review aims to clarify how energy-conscious concepts are formulated and implemented in trajectory research and to classify the links between analytic–numeric optimization and reinforcement-learning-based approaches. Following PRISMA guidelines, we queried Scopus (Springer and IJRCS) for journal articles published between 2021 and August 2025 and identified 124 primary studies. A structured extraction form and a taxonomy scheme mapped each paper to four research questions: (i) energy formulation, (ii) trajectory methods, (iii) system models and evaluation setups, and (iv) research gaps and future directions. Synthesis combined descriptive statistics with matrix-based and qualitative analysis. Results show that explicit energy-conscious formulations (energy models, torque or jerk penalties, power limits) appear only in a subset of works, while most studies still optimize indirect quantities such as time, smoothness, or tracking error. One-DoF configurations are frequently used as controlled testbeds for dynamics- and analytics-based energy studies. Kinematic or trajectory-based analytics and dynamics dominate the corpus (proportions 0.77 and 0.60), whereas hybrid, numeric and heuristic, and ML- or RL-based methods are less prevalent. Among the 22 studies that explicitly address energy-conscious aspects, these proportions increase to 0.96 and 0.86, indicating that analytic–dynamic formulations currently form the backbone of energy-efficient trajectory research while leaving substantial room for deeper integration between trajectory optimization and learning-based control. The review outlines priorities for multi-DoF energy models, real-time control, and energy-aware RL.

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1. Introduction

As the use of robotic arms in manufacturing and service domains continues to expand, the energy efficiency of manipulator motion is no longer merely a technical detail, but a strategic factor that affects operating cost, reliability, and system sustainability [11], [36], [64], [75]. Robot arms with 1–6 DoF are widely deployed for pick-and-place tasks [1], [3], [4], [80], [130], welding and material processing [18], [27], [63], [101], high-speed operations under torque and jerk limits [35], [37], [76], as well as service and collaborative tasks [41], [72], [87]. In this context, a growing number of studies have begun to incorporate energy-conscious aspects through energy modeling, torque/velocity/jerk penalties, and power constraints [36], [64], [75], [126]. However, their formulation approaches and evaluation schemes remain scattered across platforms, DoF configurations, and task types.

Although the number of publications on energy-efficient trajectories and energy-aware control continues to increase [36], [64], [75], [91], the research landscape remains fragmented by method type—ranging from classical analytic and dynamic schemes [1], [3], [22], [39], to numerical and heuristic methods [27], [73], [77], [110], and machine-learning and reinforcement-learning approaches [68], [70], [91], [98]—as well as by DoF configuration and validation scheme (pure simulation, real experiments, or a combination) [4], [20], [41], [92], [97]. Existing reviews generally discuss energy efficiency at the level of manufacturing cells or production systems more broadly, rather than specifically synthesizing how energy is modeled and optimized in manipulator trajectory planning [9], including its integration with RL. Therefore, this systematic literature review is designed to address: (RQ1) how recent studies formulate and integrate energy aspects in trajectories; (RQ2) which trajectory methods are used and what their main characteristics are; (RQ3) which manipulator types, system models, tasks, and validation schemes are dominant; and (RQ4) what key gaps and future research directions emerge from this corpus. To date, no systematic review article has been identified that specifically examines energy-conscious aspects of the trajectory methods employed in robotic manipulators.

This review contributes by constructing a structured map of energy-aware trajectory planning and control for robotic manipulators based on 124 identified primary studies. Specifically: (i) it formulates a taxonomy of energy-conscious trajectory formulations (energy models, power limits, torque/jerk penalties) [36], [64], [75], [100], [126]; (ii) it maps the spectrum of trajectory methods—from dynamics and analytics to numerical, heuristic, and RL/hybrid approaches [1], [3], [37], [68], [70], [91]—along with their distribution over DoF and task categories; (iii) it analyzes the relationship between methods and validation schemes (simulation, real, and sim+real) [4], [41], [43], [92], [97]; and (iv) it proposes a research agenda highlighting the need for multi-DoF energy modeling, real-time implementation, and the integration of energy-aware reinforcement learning for more realistic and multi-objective industrial tasks [64], [91], [100], [126].

2. Method

2.1. Research Methodology

In conducting this review, we followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework [19], [127]. The search-term formulation strategy was designed to identify key concepts derived from the research questions, with a focus on interventions (optimization and modeling approaches) and outcomes (energy efficiency and validation performance). Synonyms and related terminology were linked using the Boolean operator OR, while the main thematic dimensions were combined using Boolean AND. To ensure comprehensive coverage, the following search query was developed and refined through several iterations:

- Query on Springer databases: ("energy" OR "energy consumption" OR "energy-efficient" OR "minimize power") AND ("trajectory" OR "trajectories" OR "trajectory planning" OR "motion planning" OR "movement strategy") AND ("manipulator" OR "robot arm" OR "industrial robot" OR "robots" OR "DOF") AND ("optimization" OR "reinforcement learning" OR "machine learning" OR "deep reinforcement learning").

- Query on IJRCS databases: ("robotic arm" OR "manipulator").

The combination of search strings was designed so that the resulting corpus would remain comprehensive yet focused, namely publications that directly address energy consumption modeling, trajectory optimization, and learning-based control for robotic manipulators. Various synonyms and spelling variants were included to minimize the risk of missing relevant studies and to broaden coverage across subfields of robotics and energy optimization. The search was carried out systematically on Scopus-indexed databases, namely Springer Nature journals (quartiles 1–4) and the International Journal of Robotics and Control Systems (IJRCS, quartile 3). Only peer-reviewed journal articles published between January 2021 and August 2025 were included, with two additional articles from September 2025 added to align with the temporal scope. Conference papers, theses, dissertations, and book chapters were excluded to maintain consistency and quality. Articles retrieved by the query that were closed access (<7% of the 143 initially selected articles) were placed in the exclusion category.

Fig. 1 presents the PRISMA diagram [119] summarizing the literature selection flow. The initial search using the query string yielded 1,364 publications. The next stage was keyword-based screening, with terms grouped into: (1) Energy ("energy consumption", "minimize power", "energy-efficient"), (2) Trajectory ("trajectories", "trajectory planning", "movement strategy"), and (3) Manipulator ("manipulators", "robot arm", "robots", "reinforcement learning"). At this stage, 1,233 articles and a further 19 were manually set aside as suboptimal or because their titles were insufficiently relevant to the focus of the review. A total of 124 studies were retained for in-depth analysis and were classified into three main categories: (A) energy and power consumption (22 studies), (B) trajectory and movement strategy (74 studies), and (C) manipulators, robot arms, and reinforcement learning (42 studies).

Prisma Diagram Block

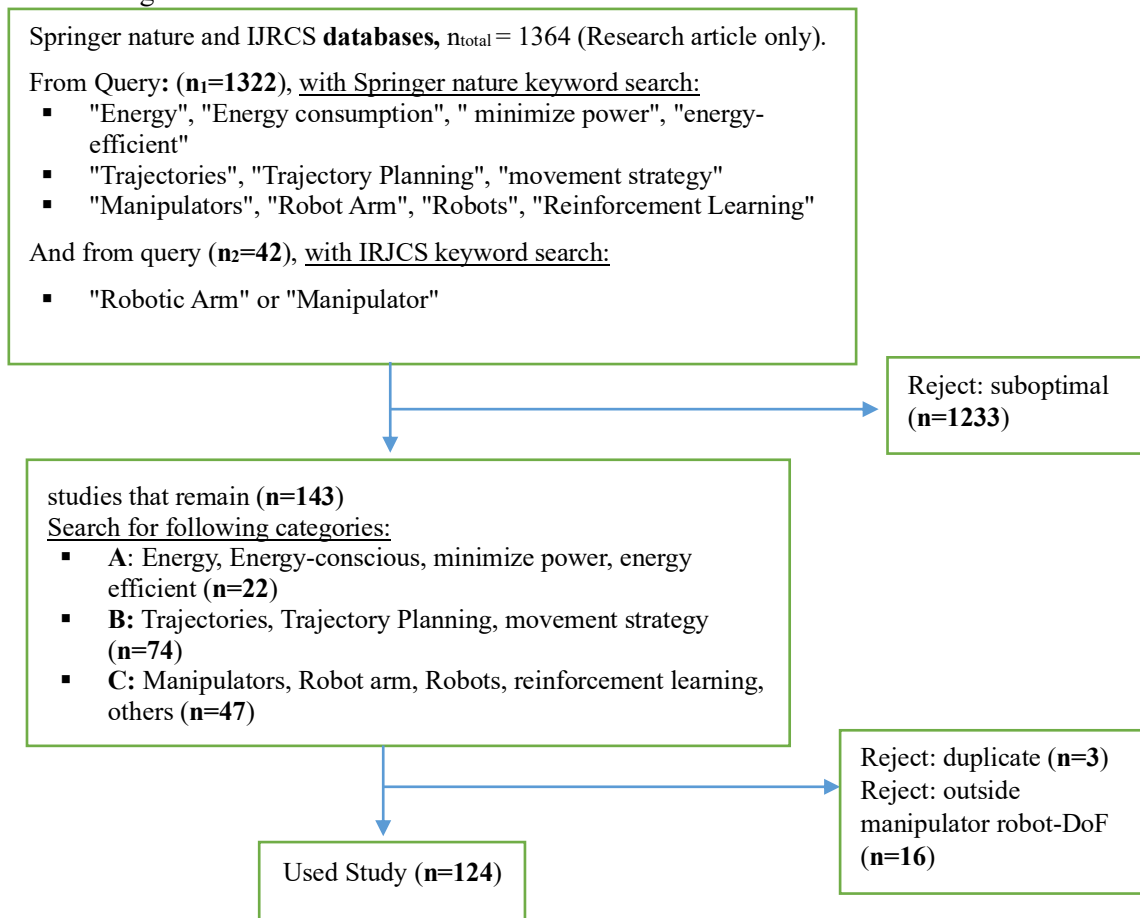


Fig. 1. PRISMA flowchart

2.2. Inclusion criteria

The inclusion and exclusion criteria in this study were designed to maintain the focus and quality of the analyzed corpus and are presented in [Table 1](#).

Table 1. Listing of inclusion and exclusion criteria

| No. | Inclusion Criteria | Exclusion Criteria |
|-----|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------|
| 1 | Studies published between 2021 and August 2025 | Studies published before 2021 |
| 2 | Research focusing on energy consumption of robot arm/manipulator trajectories using nonlinear, heuristic, or reinforcement learning (RL) methods | Research focused on other unrelated domains |
| 3 | Studies published in peer-reviewed journals indexed in the Springer Nature and IJRCS databases (Q1–Q4) and available for download | Studies published in conference proceedings or in other journal databases |
| 4 | Publications written in English | Publications not written in English |
| 5 | Research investigating trajectory tracking tasks with an energy consumption model for robots/manipulators with various Degrees of Freedom (DoF) and methods, particularly those using dynamic or kinematic modeling, heuristic or ML/RL approaches, and simulation and/or real validation | Research that investigates topics outside this scope, including robots that are not manipulator arms |

2.3. Quality Assessment

In addition to the inclusion and exclusion criteria, the quality assessment process plays a crucial role, as evaluating the rigor of the primary studies is key to ensuring the overall validity of the review's findings. Quality assessment indicators are used to support the data synthesis stage, where each study is synthesized and classified to determine its contribution to the review objectives. This evaluation also serves to assess the strength of the conclusions and the reliability of the result interpretations [131]. The assessment was carried out using a three-level scale designed to measure the extent to which each article meets the predefined quality criteria. The category "Yes" (Y) indicates full compliance with the criterion, "Partly" (P) indicates partial compliance, and "No" (N) indicates that the article does not meet the criterion. The results of this assessment process are presented in [Table 2](#). Furthermore, the data extraction framework with comparative analysis was applied consistently by a single researcher to maintain uniformity of evaluation across studies. Data were collected using a worksheet with a clear structure and predefined columns for each variable.

Table 2. Quality assessment criteria for 124 reviewed studies

| No. | Quality Assessment Criteria | Y | N | P |
|-----|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----|---|---|
| C1 | Do the selected papers explicitly implement or analyze energy-conscious trajectory/control techniques falling under Dynamics, Kinematics–Trajectory-based Analytics, Numeric & Heuristics, or ML & RL-based methods? | 122 | 2 | 0 |
| C2 | Are the proposed methods or models evaluated through comparison with baseline approaches or reference methods to validate performance improvement? | 124 | 0 | 0 |
| C3 | Do the selected papers explicitly implement validation based on Simulation, Real Experiments, or a combination of Simulation + Real? | 124 | 0 | 0 |
| C4 | Is the effectiveness of the proposed techniques evaluated using performance metrics (energy, trajectory accuracy, torque, velocity, acceleration, or computation time) documented in the synthesis table? | 124 | 0 | 0 |

Y (Yes): The study fully covers the relevant quality criterion; N (No): The study does not cover the relevant quality criterion; P (Partially): Partially satisfies or insufficiently described.

2.4. Analysis Categories

To guide the review process in a structured manner and ensure that each stage of the analysis remains aligned with the research objectives, the next step focuses on formulating the Research Questions (RQs). These review questions serve as the main guideline that directs the entire Systematic Literature Review (SLR) process [131]. For the Research Questions (RQ) formulation, the questions and their underlying motivations are presented in [Table 3](#).

In this study, the research questions are formulated with reference to the PICOC structure (Population, Intervention, Comparison, Outcome, Context), as recommended by [131], to sharpen the focus of the review. The Population (P) in this review consists of scientific studies on robotic arms and manipulators (with various DoF and tasks, as summarized in the "Task and Manipulator DoF" column in Table X) that aim to improve motion efficiency and/or trajectory performance. The Context (C) is limited to publications that address energy-aware trajectory planning and dynamic/kinematic modeling for robotic manipulators.

Table 3. Research questions and motivation

| RQ- | Research Question (RQ) | Motivation |
|------|----------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| RQ-1 | How do recent studies formulate and integrate "energy-conscious" aspects in trajectory planning and control methods for robotic manipulators? | To concisely understand how energy efficiency is formalized (energy models, power/torque limits, jerk penalties) so that diverse studies can be compared within a common formulation framework. |
| RQ-2 | What methods are used to construct energy-conscious trajectories for robotic manipulators, and what are the main characteristics of each approach? | To map analytic, numeric/heuristic, ML/RL, and hybrid methods together with their model requirements, computational load, and multi-objective capability as a basis for selecting or combining methods. |
| RQ-3 | What types of manipulators, system models, task scenarios, and evaluation environments are predominantly used in energy-conscious trajectory planning studies? | To describe the testing context (robot type, DoF, model, task, simulation vs real) and identify application areas or manipulator types that remain underexplored. |
| RQ-4 | What are the main limitations and research gaps in the energy-efficient trajectory literature, and what future research directions are promising? | To summarize recurring limitations into explicit research gaps and outline a forward-looking research agenda for energy-efficient trajectory planning. |

For RQ-1, the most relevant PICOC components are Intervention (I) and Outcome (O). The Intervention is represented by the "Energy-conscious" column together with the paired columns "Dynamics" and "Kinematics–Trajectory based" (Analytics, Numeric & Heuristics, ML & RL-based, Hybrid), which indicate how the studies model and incorporate energy aspects (through dynamic/kinematic models or data-driven approaches) into trajectory planning and control. The expected Outcome is a clear classification of energy formulations and how they are integrated into trajectories. For RQ-2, the main focus is Intervention (I), made explicit through the four subcolumns under Kinematics–Trajectory based: Analytics, Numeric & Heuristics, ML & RL-based, and Hybrid. These four categories form the basis for mapping the spectrum of methods for constructing energy-aware trajectories and comparing key characteristics of each group (e.g., dependence on system models, deterministic vs data-driven nature [129], and hybrid integration potential). The Outcome here is a frequency and distribution map of each method family.

In RQ-3, the dominant PICOC elements are Intervention (I) and Context (C), reflected in the "Task and Manipulator DoF" column and the three validation-environment columns ("Simulation only", "Real only", "Sim + Real"). Through these columns, Table X describes the system configurations (manipulator type, number of DoF, task type) and evaluation schemes (simulation, real experiments, or hybrid) used in energy-conscious trajectory planning studies. The Outcome is the identification of dominant configuration patterns and evaluation environments. RQ-4 primarily uses Outcome (O) in a narrative synthesis, by aggregating the limitations and research gaps reported in each study and linking them to the information in Table 5 (method type, model, and evaluation setup). This RQ is not mapped to a single column but emerges as a cross-row summary that integrates findings from RQ-1 to RQ-3 to formulate a forward-looking research agenda. The Context (C) thus encompasses academic publications from 2021 to August 2025 that address energy-aware trajectory planning and dynamic modeling for robotic manipulators.

Fig. 2 illustrates how the distribution of primary methods differs between studies that explicitly focus on energy-aware trajectories (Energy-conscious, RQ set) and the remaining studies in the corpus. The left bar (22 papers) shows that most energy-conscious studies rely on Dynamics and Numeric & Heuristics as primary methods, with additional contributions from ML & RL-based approaches and only a small portion that depend purely on Analytics (Kinematics–Trajectory based).

This is consistent with the need for more physically grounded energy modeling, since energy optimization almost always requires access to torque, force, or power information derived from dynamic models or numerical optimization built on top of them. In contrast, the right bar (102 non-energy papers) shows a more "spread-out" distribution: Numeric & Heuristics and ML & RL-based methods dominate, followed by Dynamics and Analytics, with a single Hybrid study and only two unclassified papers (Unspecified).

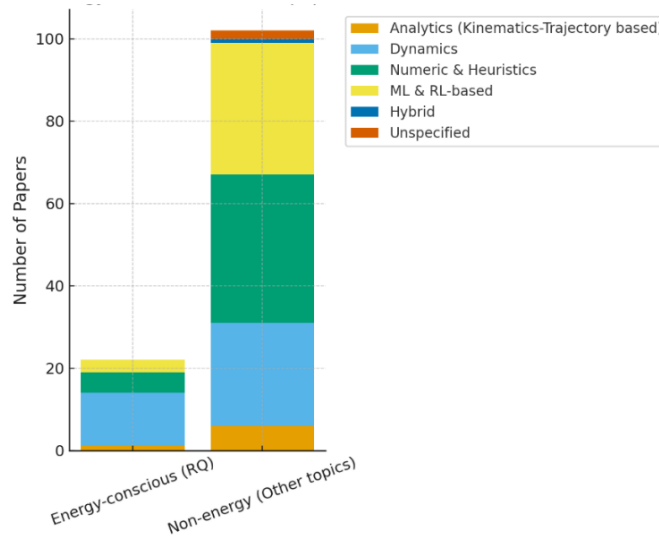


Fig. 2. Distribution of paper reference in 5 years (2021-2025) with energy-conscious

This pattern indicates that, outside the energy focus, the research community tends to explore data-driven learning and heuristic optimization methods for a variety of other objectives (accuracy, speed, obstacle avoidance, etc.), while energy-conscious studies remain relatively more "conservative" and concentrated around dynamics + numerical optimization. Thus, the chart reinforces the RQ-2 finding that the current method spectrum for energy-efficient trajectories is still centered on model-based and numerically optimized approaches, whereas full integration with ML/RL and hybrid schemes is only beginning to emerge and offers substantial room for further exploration.

3. Results and Discussion

Each study was mapped to a trajectory-method category (Dynamics, Trajectory-based Analytics, Numeric & Heuristics, ML & RL-based, and Hybrid), and then, for each method, we identified which works explicitly addressed energy-conscious aspects. Next, the validation scheme data (Simulation, Real, Simulation + Real) were incorporated, as summarized in Table 4. The synthesis and checkboard classification show that analytics and dynamics approaches dominate across all clusters, while numeric, heuristic, and RL/hybrid methods appear more selectively—for example in studies on speed-profile optimization, jerk-bounded planning, or RL-based control for complex gait and tracking. This mapping also reveals the distribution of task types (pick-and-place, obstacle avoidance, welding, crane, biped gait, etc.) and the DoF range (1–7 DoF and special configurations >7 DoF), with a strong tendency toward 1–6 DoF manipulators as the main testbeds.

Table 4. Synthesis structured extraction sheet manipulator arm trajectory method and energy-conscious

| Ref., year (1) | Task and Manipulator DoF (2) | (3) | (4) | Kinematics-Trajectory based (5) | | | | Validation (6) | | |
|----------------------|-------------------------------------------------|-----|-----|---------------------------------|-----|-----|-----|----------------|-----|-----|
| | | | | (A) | (B) | (C) | (D) | (A) | (B) | (C) |
| [1], 2025 | Time-optimal planning, serial 6-DoF | | | X | X | | X | X | | |
| [2], 2025 | Obstacle-avoidance optimization, SCARA 3-DoF | | | X | X | | | X | | |

| Ref., year (1) | Task and Manipulator DoF (2) | (3) | (4) | Kinematics-Trajectory based (5) | | | | Validation (6) | | |
|----------------------|---------------------------------------------------------------|-----|-----|------------------------------------|-----|-----|-----|----------------|-----|-----|
| | | | | (A) | (B) | (C) | (D) | (A) | (B) | (C) |
| [3], 2025 | Parabolic-ramp planning, Cartesian 2-axis pick-place | X | X | X | | | | X | | |
| [4], 2025 | Delta 3-DoF pick-place dynamics validation | | X | X | | | | | | X |
| [5], 2025 | Trajectory tracking for 5-DoF arm | | | | | X | | X | | |
| [6], 2022 | Singularity-robust IK, Stanford 6/7-DoF | | X | X | X | | X | X | | |
| [7], 2023 | Data-driven dynamics modeling, SCARA 4-DoF | | X | | X | | | | | X |
| [8], 2023 | Cooperative planning, multi-robot welding collision-avoidance | | X | X | X | | X | X | | |
| [10], 2025 | Circular trajectory tracking, Delta 3-DoF | | X | X | | X | X | X | | |
| [11], 2024 | Energy-aware dynamics modeling, ABB 6-DoF | X | X | X | | | | X | | |
| [12], 2025 | Path planning and smoothing, 6-DoF | | X | X | X | | X | X | | |
| [13], 2025 | Redundant 7-DoF pick-weld trajectory planning | | X | X | X | | X | | | X |
| [14], 2025 | Trajectory tracking, SCARA 2-DoF | | X | X | | | | X | | |
| [15], 2025 | Stewart platform 6-DoF tracking control | | X | | | X | | X | | |
| [16], 2025 | Flexible 1-link end-effector tracking | | X | X | | X | X | X | | |
| [17], 2025 | Double-chain 9–12 DoF mechanism design | | X | X | X | X | X | X | | |
| [18], 2025 | Multi-robot spot welding, industrial robots | | | X | X | X | X | X | | |
| [20], 2025 | Cable-swing reduction, quadrotor plus cable | | X | X | | | | | | X |
| [21], 2025 | Industrial Fanuc 6-DoF inverse kinematics | | | X | X | | X | X | | |
| [22], 2025 | KUKA 6-DoF milling dynamics analysis | | X | X | | X | X | | | X |
| [23], 2025 | JAKA ZU7 friction-identified dynamics model | X | X | X | | | | | | X |
| [24], 2025 | Joint-fault detection across four 6-DoF | | | X | | X | X | | X | |
| [25], 2025 | Two-link 2-DoF trajectory tracking | | X | X | | X | X | X | | |
| [26], 2025 | Underactuated RIP 2-DoF swing-up stabilization | | X | X | | X | X | | X | |
| [27], 2025 | Grinding complete coverage path planning | X | X | X | | X | X | | | X |
| [28], 2025 | SIASUN 7-DoF grasping planning control | | | | | X | | | | X |
| [29], 2025 | Real-time monitoring and fault prediction | | | | X | X | X | X | | |
| [30], 2025 | UR5 6-DoF obstacle-avoidance trajectory planning | | | | | X | | X | | |
| [31], 2025 | Time-optimal planning for Xarm6 6-DoF | | | | X | | | | | X |
| [32], 2024 | UR5e 6-DoF material-handling avoidance planning | | | X | X | | X | | | X |
| [33], 2025 | Robust tracking and rejection, SCARA 2-DoF | | X | X | | X | X | X | | |
| [34], 2024 | Pan-tilt 2-DoF end-effector visual tracking | | | | X | | | | | X |

| Ref., year (1) | Task and Manipulator DoF (2) | (3) | (4) | Kinematics-Trajectory based (5) | | | | Validation (6) | | |
|----------------------|--------------------------------------------------|-----|-----|------------------------------------|-----|-----|-----|----------------|-----|-----|
| | | | | (A) | (B) | (C) | (D) | (A) | (B) | (C) |
| | | | | (A) | (B) | (C) | (D) | (A) | (B) | (C) |
| [35], 2024 | Speed-profile selection, 1-DoF point-to-point | X | X | X | | | | X | | |
| [36], 2024 | Energy-efficient high-speed Delta pick-place | X | X | | X | | | X | | |
| [37], 2024 | Smooth time-optimal prismatic 2-axis planning | | X | X | | | | | | X |
| [38], 2024 | Torque-driven 2-DoF joint-space tracking | X | X | X | | | | | X | |
| [39], 2024 | Planar 4R 4-DoF obstacle avoidance | | X | X | | X | X | | | X |
| [40], 2024 | Two-servo planar 2-DoF manipulator control | | X | X | | | | X | | |
| [41], 2024 | Outer-loop NN control, UR5e/UR10e 6-DoF | | X | X | | X | X | | X | |
| [42], 2024 | Free-load path planning, JAKA 6-DoF | | | X | X | | X | | | X |
| [43], 2024 | Container-crane anti-sway trajectory planning | | X | X | | | | X | | |
| [44], 2024 | RGB object pose tracking, 6-DoF | | | X | X | | | | | X |
| [45], 2024 | MRM 2-DoF joint tracking, friction | | X | X | X | X | | | | X |
| [46], 2024 | Uneven-terrain humanoid navigation, ~21-DoF | | | | X | X | X | | | X |
| [47], 2023 | Frictional dynamics modeling, 1-DoF link | | X | X | X | | X | | | X |
| [48], 2024 | Bimanual pick-place sequencing, YuMi 14-DoF | | | | X | | | | | X |
| [49], 2024 | Compliant mechanism design, planar 2-DoF | | | X | X | | X | | | X |
| [50], 2024 | Offline PID tuning for 1R/2R/6R | | X | X | X | | X | X | | |
| [51], 2024 | Surgical motion constraint, 7-DoF robot | | X | X | | | | | | X |
| [52], 2024 | XR evaluation of HRC planning | | | | | X | | X | | |
| [53], 2024 | Single-iteration learning, 6-DoF tracking | | X | X | | | | | | X |
| [54], 2024 | TBM steel-arch splicing trajectory control | | X | X | | | | | X | |
| [55], 2024 | Three-link PPA swing-up stabilization | X | X | X | | | | X | | |
| [56], 2024 | Manufacturing power and energy estimation, xArm7 | X | | X | X | | y | | | X |
| [57], 2023 | ML-based smart fabrication monitoring, UR5 | | | | | X | | | | X |
| [58], 2024 | Motor-current state prediction, SCARA 4-axis | | | | X | X | X | | X | |
| [59], 2024 | Pose adjustment and vibration reduction, 6-PRSS | | X | X | X | | X | X | | |
| [60], 2024 | Hexapod foot placement, 18-DoF stability | | | | X | X | X | | | X |
| [61], 2024 | Motion planning in cluttered environments | | | | | X | | X | | |
| [62], 2024 | Robot dynamic parameter identification | | X | X | | | | | X | |
| [63], 2024 | Grinding seam path/posture planning, ABB 6-DoF | | | X | | | | | | X |
| [64], 2025 | Energy-efficient PTP planning, industrial 6-DoF | X | X | X | | X | X | | | X |

| Ref., year (1) | Task and Manipulator DoF (2) | (3) | (4) | Kinematics-Trajectory based (5) | | | | Validation (6) | | |
|----------------------|----------------------------------------------------------------|-----|-----|------------------------------------|-----|-----|-----|----------------|-----|-----|
| | | | | (A) | (B) | (C) | (D) | (A) | (B) | (C) |
| [65], 2023 | Forward/inverse kinematics, 3-DoF RRR | | | | | X | | X | | |
| [66], 2024 | IK and pose control, 6-DoF digital twin | | | | | X | | | | X |
| [67], 2024 | Safe planning with moving obstacles, ABB 6-DoF | | | | | X | | X | | |
| [68], 2024 | Continuous-control RL in simulated environments | | | | | X | | X | | |
| [69], 2025 | Edge path tracking, UR5 6-DoF | | | | | X | | | | X |
| [70], 2023 | Deep RL reach-grasp-lift, Panda 7-DoF | | | | | X | | X | | |
| [71], 2024 | Control and gain selection, 6-DoF | | | | | X | | X | | |
| [72], 2024 | Vision-based HRC obstacle avoidance, UR5/KUKA | | | X | | | | | | X |
| [73], 2023 | Speed-profile saturation strategy, 1-DoF axis | X | X | X | | | | X | | |
| [74], 2023 | Multi-point IK optimization, KUKA 6- DoF | X | | X | X | | X | X | | |
| [75], 2024 | Arc-welding energy modeling, ABB 6- DoF | X | X | X | | | | | | X |
| [76], 2023 | Jerk-bounded planning, underactuated flexible joint | | X | X | | | | | X | |
| [77], 2023 | Deposition path optimization, hexapod 6- DoF | X | | X | | | | X | | |
| [78], 2023 | Two-link planar 2-DoF tracking | | X | X | | | | X | | |
| [79], 2023 | Rail robot 3-DoF time-optimal planning | | | | | X | | | | X |
| [80], 2024 | Servo-based 5-DoF arm pick-place | | | X | | | | | X | |
| [81], 2025 | Flexible-link control and vibration suppression | | | X | X | | X | X | | |
| [82], 2023 | Underactuated 4-DoF inverse dynamics, singularity avoidance | | X | X | | | X | X | | |
| [83], 2023 | Bourdon-tube elastic joint kinematic control | | X | X | | | | X | | |
| [84], 2023 | Elastic-joint robot hysteresis dynamics identification | X | X | X | | | | | | X |
| [85], 2023 | Nonholonomic unicycle 3-DoF source seeking | | | | X | | | X | | |
| [86], 2023 | Torque minimization, heavy-duty redundant 7-DoF | X | X | X | | | | | X | |
| [87], 2023 | Nonlinear tracking and rejection, 4-DoF service | | X | X | X | | X | | X | |
| [88], 2023 | Parameter identification, redundant SCARA 5-DoF | | X | X | | | | X | | |
| [89], 2024 | Bilateral teleoperation force-position coordination | | X | X | | | | | | X |
| [90], 2023 | Safe C-space planning with clearance | | | | | X | | | | X |
| [91], 2023 | Energy-optimized RL gait control, 3-DoF biped | X | X | X | | X | X | X | | |
| [92], 2023 | Digital-twin welding cell, multi-robot system | | | | | | | | | X |
| [93], 2025 | Quanser QArm 4-DoF robust tracking | | X | X | | | | X | | |
| [94], 2025 | Kinova Gen3 ball balancing, 7-DoF | | | X | | X | X | X | | |

| Ref., year (1) | Task and Manipulator DoF (2) | (3) | (4) | Kinematics-Trajectory based (5) | | | | Validation (6) | | |
|----------------------|----------------------------------------------------------------|-----|-----|------------------------------------|-----|-----|-----|----------------|-----|-----|
| | | | | (A) | (B) | (C) | (D) | (A) | (B) | (C) |
| [95], 2024 | Constrained rigid-flexible multibody dynamics modeling | | X | X | | | | X | | |
| [96], 2023 | Flexible two-link tracking and vibration suppression | | X | X | | | | X | | |
| [97], 2024 | Virtual prototyping/commissioning, ABB robotic cell | | | | | | | | | X |
| [98], 2023 | Swarm speed forecasting, foot-bot robots | | | | | X | | X | | |
| [99], 2024 | Coordinated dual-arm task-space tracking, 4-DoF | | X | X | X | | X | X | | |
| [100], 2023 | Space manipulator failure control, energy optimization | | | | X | X | | X | | X |
| [101], 2023 | Chainsaw robot planning, KUKA 6-DoF | | X | X | X | | X | X | | |
| [102], 2025 | Two-link RR 2-DoF robust tracking | | X | X | | | | X | | |
| [103], 2022 | Kinematics and planning, 6/7-DoF arms | | | | X | X | | X | X | |
| [104], 2023 | Point-to-point planning, planar 2-DoF plus 6-DoF | X | X | X | | | | X | | |
| [105], 2022 | 6R joint-space planning with jerk limits | | | | X | X | | X | X | |
| [106], 2025 | 6-DoF arm design, fabrication, evaluation | | | | X | | | | | X |
| [107], 2022 | Online dynamics identification and adaptive control | | X | X | | X | | X | | X |
| [108], 2022 | Unmanned shovel digging trajectory, 2- DoF | X | X | X | X | | | X | | X |
| [109], 2022 | Underactuated planar PUM posture control | | X | X | | | | X | | |
| [110], 2022 | Obstacle avoidance with near time- optimal planning | | X | X | X | | | X | X | |
| [111], 2022 | Hybrid humanoid-arm multi-objective planning, ~7-DoF | | X | X | X | | | X | X | |
| [112], 2022 | Hybrid spray-painting robot tracking accuracy | | X | X | | | | | | X |
| [113], 2022 | Underactuated tower crane nonlinear anti-sway | | X | X | X | | | X | X | |
| [114], 2022 | Workcell layout and trajectory optimization | X | X | X | X | | | X | | X |
| [115], 2023 | Reliability-based optimal design, flexible-link manipulator | | X | X | X | | | X | X | |
| [116], 2020 | EDM milling trajectories using 6-DoF robot | | | | X | | | | X | |
| [117], 2022 | Singularity-free IK and joint prioritization | | X | X | | | | X | | |
| [118], 2022 | Space-debris docking, cooperative planar manipulators | | X | X | X | | | X | X | |
| [120], 2022 | Underactuated planar 3-DoF fault- tolerant tracking | | X | X | | | | | | X |
| [121], 2022 | Smooth planning and singularity avoidance, 7R arm | | X | X | X | | | X | X | |
| [122], 2022 | Cartesian workspace planning, Walker2 arm 7-DoF | | | | | X | | | | X |
| [123], 2022 | Parallel planar 3-DoF end-effector tracking | | X | X | | | | | | X |
| [124], 2022 | 3D path planning for UR5 6-DoF | | | | X | X | | X | | X |
| [125], 2022 | Variable-stiffness prosthesis joint tracking, 1-DoF | | X | X | | | | | | X |

| Ref., year (1) | Task and Manipulator DoF (2) | (3) | (4) | Kinematics-Trajectory based (5) | | | | Validation (6) | | |
|----------------------|----------------------------------------------------|-----|-----|------------------------------------|-----|-----|-----|----------------|-----|-----|
| | | | | (A) | (B) | (C) | (D) | (A) | (B) | (C) |
| [126], 2023 | Energy-saving PTP optimization, 1-DoF axis | X | X | X | | | | | | X |
| [128], 2021 | SCARA pick-place kinematic design, planar 2-DoF | X | X | X | | | | X | | |

Column note: (3): Energy-conscious; (4): Dynamics; (5-A): Analytics; (5-B): Numeric and Heuristics; (5-C): Machine Learning (ML) and Reinforcement Learning (RL); (5-D): Hybrid (6-A): Simulation; (6-B): Real; (6-C): Sim+Real;

3.1. Research Question (RQ-1)

RQ-1: How do recent studies formulate and integrate "energy-conscious" aspects in trajectory planning and control methods for robotic manipulators (e.g., via energy models, power limits, torque/velocity/jerk penalties, or other energy indices)?

Fig. 3 can be read as a visual framework for answering RQ-1. On the left, the *Kinematics and Trajectory* block generates joint trajectories $\theta_1(t)$, $\theta_2(t)$, ..., $\theta_n(t)$ from the desired end-effector motion. These trajectories are then "sent" to the right-hand side, the robot arm *kinetics-dynamics* model, which computes joint torques, forces, and dynamic responses. The green layer in the middle (*Energy consumption measurement and conscious*) represents where different studies formulate energy: some use explicit energy or power models based on torque-velocity, while others add power/torque limits or penalties on jerk and smoothness of $\theta(t)$. The bottom boxes (Analytics, Numeric and Heuristics, ML & RL, Hybrid) indicate the method families that exploit this energy information, either as an objective function, a constraint, or a reward in RL. Based on the synthesis, 22 out of 124 studies explicitly formulate energy-conscious aspects in trajectory planning and control. Among these, the most common approach is to construct an energy or power model from trajectory dynamics (e.g., torque-velocity integrals, mechanical work, or actuator power estimates) and incorporate it as the main objective or as one term in a multi-objective cost. Other studies do not model energy directly but encode efficiency through power/torque limits, penalties on velocity, acceleration, and jerk, or smoothness indices assumed to correlate with energy use and mechanical load.

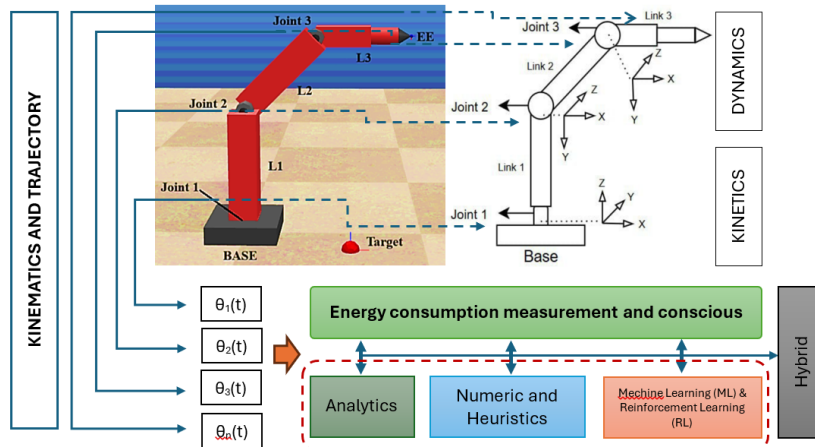


Fig. 3. Illustration of the taxonomy for measuring energy-conscious trajectory parameters

In several RL-based studies, energy-conscious behavior is integrated via reward shaping, for example by penalizing high torque, strong velocity fluctuations, or excessive motion duration. These formulations appear in various forms: adding energy terms to the cost function, enforcing torque/power and jerk constraints, or defining composite indices that balance energy, time, and tracking error. This pattern shows that although the mechanisms for incorporating energy are becoming more diverse, fully explicit and systematic energy formulations in trajectory planning are still confined to a small subset of the corpus, while most studies rely on surrogates such as time, smoothness, and tracking error. The resulting taxonomy helps normalize how different studies interpret "energy-efficient," making cross-method comparison easier and providing a basis for

designing future energy formulations. Thus, Fig. 3 positions "energy formulation" as an intermediate impact layer between kinematic–dynamic trajectories and the spectrum of optimization/control methods.

3.2. Research Question (RQ-2)

RQ-2: What methods are used to construct energy-conscious trajectories for robotic manipulators (analytic, numeric, heuristic, and Reinforcement Learning), and what are the key characteristics of each approach?

Addressing RQ-2, Fig. 4 compares the distribution of method categories between energy-conscious and non-energy studies. Across all 124 reviewed papers, kinematics–trajectory-based (analytics) and dynamics methods dominate the corpus, being used in 95 and 74 studies (about 76.6% and 59.7%), respectively. Hybrid, numeric & heuristics, and ML & RL-based approaches appear less frequently, with proportions of 41.1%, 38.7%, and 28.2%. When the focus is restricted to the 22 explicitly energy-conscious studies, this dependence becomes even stronger: approximately 95.5% of them employ analytics and 86.4% dynamics, while hybrid, numeric & heuristics, and ML & RL-based methods are present in only 31.8%, 22.7%, and 13.6% of the cases. These patterns indicate that analytic–dynamic formulations currently form the main foundation for designing energy-efficient trajectories, whereas numeric, heuristic, and RL-based approaches are emerging more as complementary layers that expand the optimization and adaptation space of the system.

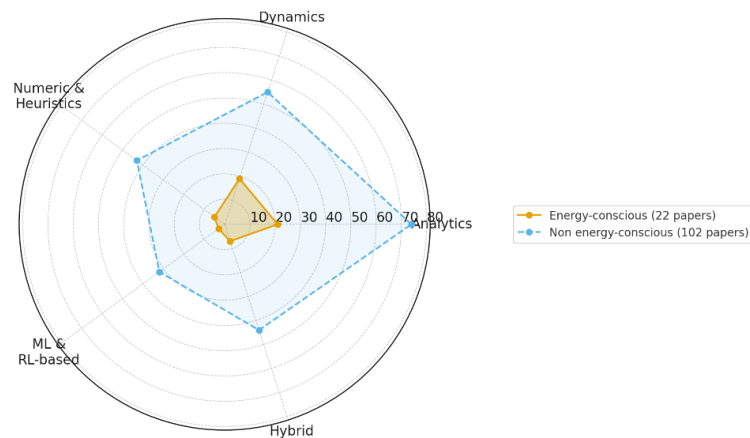


Fig. 4. Distribution of trajectory method categories in energy-conscious and non-energy studies

An overall summary of this method spectrum is that analytic–dynamic formulations remain the backbone, while numeric, heuristic, and RL-based approaches act as additional optimization layers to handle nonlinearity, multi-objective trade-offs, and adaptation under more complex operating conditions.

3.3. Research Question (RQ-3)

RQ-3: What types of manipulators, system models (kinematic, dynamic, or empirical), task scenarios (pick-and-place, welding, crane, mobile–manipulator), and evaluation environments (simulation vs real) are predominantly used in energy-conscious trajectory planning studies?

Addressing RQ-3, Fig. 5 shows how the 124-study corpus maps trajectory research onto different manipulator configurations and tasks. Most works focus on arms with 1–7 DoF, with 6-DoF manipulators appearing most frequently (42 studies), followed by 2-DoF (19) and 3-DoF (13), which are often used as controlled testbeds. Other configurations—1-DoF (8 studies), 4-DoF (9), 5-DoF (4), and higher-DoF systems such as 12-, 16-, and 21-DoF (one study each)—complete the spectrum, while 16 studies do not explicitly specify the DoF.

In terms of task scenarios, 54 studies are classified as generic trajectory/path tracking and 25 as pick-and-place, followed by 16 welding/printing cases, 9 HRI/collaborative tasks, and a smaller number of crane, coverage/inspection, and multi-robot applications.

At the method level, kinematics–trajectory-based (analytics) and dynamics-based approaches are used in 95 and 74 studies, respectively, while numeric & heuristics (48 studies), ML & RL-based (35 studies), and hybrid methods (51 studies) add further variety in optimization and learning strategies. Taken together, these figures indicate that analytic–dynamic formulations still constitute the primary foundation, with numeric, heuristic, and machine-learning methods employed in various combinations of tasks and DoF configurations, leaving substantial room for further hybrid exploration.

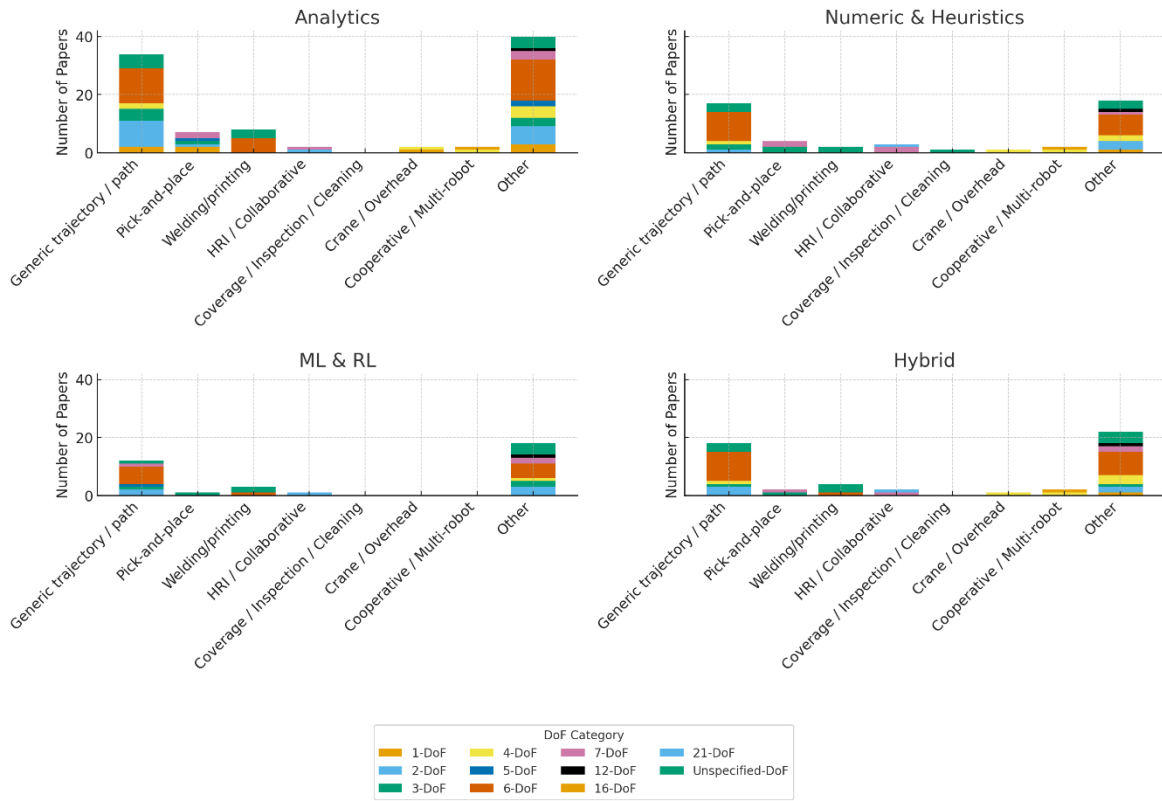


Fig. 5. Distribution of task category and DoF-manipulator

Fig. 6 presents a combined view of trajectory method categories and validation types (simulation only, real only, and simulation + real). Purely simulation-based validation dominates across all methods: about 50–57% of studies in analytics (50 of 95), dynamics (41 of 74), numeric & heuristics (25 of 48), ML & RL-based (19 of 35), and hybrid (29 of 51) are tested only in simulated environments. By contrast, combined simulation + real experiments constitute the second-largest portion, ranging from roughly 33–44%; for example, 34 analytics studies, 25 dynamics, 21 numeric & heuristics, 12 ML & RL, and 17 hybrid studies conduct validation in both environments.

Meanwhile, *real-only* validation is relatively rare, generally in the range of 4–12% for each method category (11 analytics studies, 8 dynamics, 2 numeric & heuristics, 4 ML & RL, and 5 hybrid). Although the number of studies that already include physical validation can be considered adequate, further research that enriches the scenarios and depth of simulation-based validation is still needed as a fundamental foundation before real-world testing, so that model precision can be improved and potential loss-cost at the physical implementation stage can be minimized.

3.4. Research Question (RQ-4)

RQ-4: What are the main limitations and research gaps in the current literature on energy-efficient trajectories—especially for multi-DoF systems, real-time operation, and the integration of analytic/numeric methods with RL—and what are the potential future research directions? The following is a synthesis of limitations by trajectory model in response to RQ-4.

3.4.1. Kinematics–Trajectory based (Analytics)

In the analytics group, most studies rely on kinematic models and ideal trajectory profiles (time-optimal, smooth profile, point-to-point) for 1–3 DoF or a single robot configuration. Many papers explicitly simplify or neglect friction, backlash, actuator saturation, and parameter uncertainty. Task environments are generally static (pick-and-place, rail robots, cranes, controlled path planning), and only a small subset extends to noisy industrial scenarios or HRC. Energy formulation often does not appear as a primary objective; trajectories are mainly optimized for time or smoothness, so energy consumption is only addressed indirectly. Validation is still largely explored at the simulation stage or in small-scale lab setups. This indicates a gap: the need for kinematic–trajectory formulations that are coupled with energy models and tested on multi-DoF manipulation under more realistic conditions.

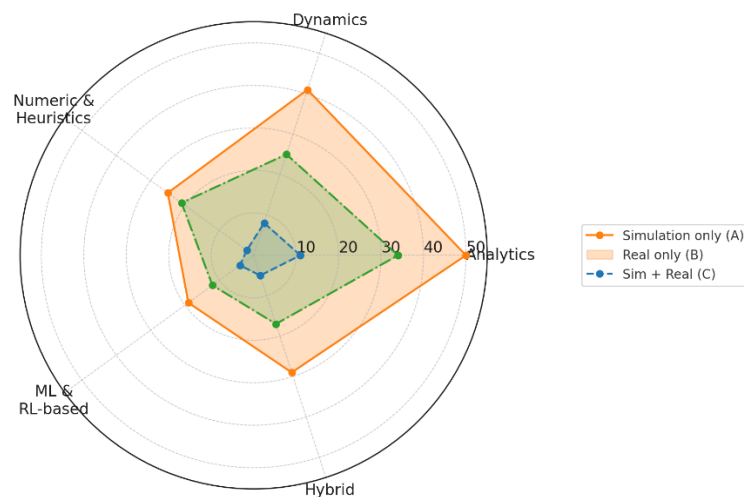


Fig. 6. Distribution of validating trajectory model

3.4.2. Dynamics-based

Dynamics-based studies typically use rigid-body models with parameters assumed known or identified for a single platform (e.g., specific ABB, KUKA, UR, or Delta robots). Friction, link elasticity, and thermal effects are usually simplified or ignored; only a few works systematically address uncertainty and large disturbances (wind on cranes, varying cutting forces, cable deformation, etc.). Many papers emphasize that validation is performed on one robot type, one task (welding, milling, arc welding, crane, shovel), and a narrow load range, which limits generalization to other configurations. Energy analysis is often not multidimensional (for example, not yet linking torque, energy, and actuator lifetime). The resulting gap is the need for richer dynamic models (flexibility, complex friction, load variation) tested systematically on multi-DoF, multi-task, and long-term operation.

3.4.3. Numeric & Heuristics

In the numeric and heuristic group (nonlinear optimization, GA, PSO, and similar), recurring limitations include sensitive parameter tuning and computational cost, which tend to confine algorithms to offline use or a few benchmark cases. Many studies report tests on only a handful of trajectories or configurations, without extensive robustness analysis against noise, load changes, or environmental variation. Energy formulations are sometimes included, but often without in-depth discussion of computational scaling when applied to long trajectories or multi-robot systems. This highlights the need for more structured heuristic designs (e.g., warm-start from analytic solutions), explicit complexity analysis, and case studies that are truly real-time.

3.4.4. ML & RL-based

The main limitation in ML & RL studies is that energy-related reward shaping is usually ad hoc; only a small portion integrates explicit energy models, power limits, and safety constraints in a unified

way. Training data also typically come from a single robot and a single type of task (reach-grasp, edge tracking, gait control), so cross-platform and cross-task generalization remains unclear. Evaluation is also narrow, focusing more on tracking error or task success than on the energy-time-accuracy trade-off. This opens space for research on energy-aware RL that is tied to dynamic models and designed from the outset for transfer to physical systems.

3.4.5. Hybrid (Analytics / Dynamics + Numeric / ML / RL)

Hybrid approaches combine the strengths of analytic/dynamic formulations with numeric, heuristic, or RL methods, but the limitations table shows that this integration is still partial. Many hybrid studies are tested only on a single platform (e.g., one welding cell, one hexapod, one humanoid, one workcell) and in controlled scenarios; full integration with production scheduling, process disturbances, and long-term energy metrics has not yet been achieved. In addition, some hybrid frameworks still do not operate in real time due to computational load and complex software architectures. Thus, the main gap in this group is the need for truly deployable hybrid architectures are capable of combining analytic models, numerical optimization, and RL online on multi-DoF manipulators in both repetitive and dynamic industrial tasks, with energy as a primary objective that is measured and validated in the field.

3.4.6. Limitations

There are also limitations in the scope of the literature sources used, as the search was focused on two reputable databases and has not yet covered all other relevant publication channels. Nevertheless, the synthesis conducted still examines the obtained corpus (2021–2025) in depth and systematically, so even though this corpus is relatively homogeneous in terms of database source, it can still be considered representative for characterizing research patterns in this domain within the scope of the databases used.

4. Conclusion

Overall, this review shows that energy-conscious concepts in trajectory planning and control for robotic manipulators are only explicitly adopted in a small subset of the corpus (22 out of 124 studies), mainly through energy models, power/torque limits, and torque or jerk penalties, while most works still focus on time, trajectory smoothness, path/task execution, and tracking error (RQ-1). At the method level (RQ-2), kinematic/trajectory-based analytics and dynamics remain the primary foundation (used in roughly three quarters and more than half of the corpus), including almost all explicitly energy-conscious studies, whereas numeric & heuristics, ML/RL, and hybrid approaches appear as complementary layers with smaller shares. From the system and evaluation perspective (RQ-3), the corpus is dominated by manipulators with 1–7 DoF, with a strong cluster around industrial 6-DoF arms, generic trajectory/path and pick-and-place tasks, and validation that is still largely simulation-centric, with only a subset advancing to combined simulation + experimental schemes. The limitations analysis (RQ-4) reveals consistent patterns: idealized models, a focus on low-DoF testbeds, implementations that are not yet fully real-time, and energy integration that remains incomplete in numeric, heuristic, and RL methods, particularly for more complex industrial scenarios.

The main contribution of this review to the engineering community is a structured map that links four key layers: energy formulation, the spectrum of trajectory methods, manipulator and task types, and validation patterns together with their limitations. This map can serve as a reference for designing more targeted future studies, for example by developing realistic multi-DoF energy models, designing real-time hybrid analytic-numeric-RL schemes, and extending validation to industrial tasks rich in disturbances and practical constraints. Thus, the review not only summarizes the current state of energy-efficient trajectory research, but also offers a conceptual framework to address the identified research gaps toward more efficient, adaptive, and deployable motion-control systems for robots in real-world environments. Nevertheless, further work is still needed to explore alternative trajectory formulations that may yield significant improvements in energy efficiency based on the combination of model families identified in this study.

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