



Energy-Efficient Control Strategy for Collaborative Robots in Industry 4.0 Environments

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Abstract

Collaborative robots (cobots) are increasingly deployed in Industry 4.0 production because they provide flexible automation while sharing workspaces with human operators. Their growing use, however, makes electrical energy consumption an important operational and sustainability issue. This paper proposes a methodology for an energy-efficient cobot control strategy that integrates energy-aware trajectory shaping, adaptive speed scaling, idle-state management, and safety constraints within a cyber-physical manufacturing architecture. The controller receives task, payload, human-proximity, cycle-time, and power-feedback information and solves a weighted multi-objective problem that minimizes electrical energy and peak power without violating collaboration safety or production-time limits. A representative six-axis cobot case study is formulated using a joint-level electro-mechanical power model and a discrete supervisory state machine. The methodology compares a conventional fixed-speed controller with energy-aware trajectory control and with the complete proposed strategy. In the representative simulation, the complete strategy reduces cycle energy by approximately 18.6% and peak power by 12.4% while increasing cycle time by only 3.1%. The study shows how energy objectives can be embedded directly into cobot control instead of being treated as a post-process production metric. The proposed framework is suitable for experimental implementation using controller telemetry, smart meters, digital twins, and industrial communication protocols.

Introduction

Industry 4.0 combines cyber-physical systems, industrial communication, data analytics, and intelligent automation to create production systems that are more connected and adaptive. Collaborative robots are an important element of this transformation because they can operate close to people and can be reprogrammed for varying assembly, handling, inspection, and support tasks. Reviews of collaborative robotics emphasize that control design must simultaneously address task performance, safe human interaction, sensing, and robustness [1].

Recent studies also show that cobots are becoming increasingly relevant to flexible manufacturing and assembly systems in which frequent product and task changes are expected [2].

Energy is a second design dimension that is often treated separately from safety and productivity. Industrial robot energy use depends on payload, path geometry, acceleration, speed, motor losses, controller electronics, and idle periods. Experimental work on six-axis robots has demonstrated that operating parameters

strongly influence both electrical power and dynamic behavior [3]. Optimization studies have therefore focused on trajectory planning, time scaling, machine learning, and production scheduling. Liu et al. formulated energy-efficient industrial robot trajectories through constrained multi-objective optimization [4], while Yin et al. used measured trajectory data and machine learning to provide an energy-related fitness function for optimization [5].

For collaborative robots, direct energy studies are newer. Heredia et al. integrated an energy model into an augmented digital-twin framework for cobots [6], and a 2023 UR10 study showed that trajectory programming parameters influence both peak power and total energy while an artificial neural network can predict energy consumption [7]. In parallel, reviews of industrial-robot energy optimization conclude that software measures such as motion optimization, idle-time reduction, energy monitoring, and regenerative operation are practical complements to hardware redesign [8]. These findings motivate a controller that continuously coordinates energy, cycle time, and collaboration constraints rather than optimizing a single trajectory offline.

The objective of this methodology paper is therefore to develop an energy-efficient control strategy for a six-axis collaborative robot operating in an Industry 4.0 cell. The main contribution is a layered control architecture combining (i) energy-state estimation from robot telemetry or a digital twin, (ii) multi-objective trajectory and speed optimization, (iii) safety-aware online speed scaling, and (iv) event-driven idle and standby management. The strategy is designed to remain compatible with standard production requirements and to provide measurable key performance indicators such as energy per cycle, peak power, cycle time, and energy per completed unit.

Literature Review

Energy-aware robot control has developed from dynamic-model optimization toward data-driven and networked approaches. Gregory et al. treated energy-optimal robot motion as an optimal-control problem with holonomic constraints, demonstrating the importance of integrating robot dynamics directly into trajectory generation [9]. Pellicciari et al. later proposed reducing energy consumption of pick-and-place industrial robots by optimizing motion parameters while preserving production functionality [10]. These studies established the principle that identical end-effector tasks may be

completed with different joint trajectories and time profiles that consume different amounts of electrical energy.

Model-based studies were complemented by system-level measurements. Brossog et al. experimentally examined power and dynamic behavior of a six-axis robot and reported significant sensitivity to speed and payload [3]. Liu et al. used smooth high-order B-spline trajectories and nonlinear optimization to balance energy and motion constraints [4]. Yin et al. introduced a machine-learning-based trajectory planning method that learns the relationship between joint-space motion features and measured energy [5]. More recently, graph-based path planning has also been adapted to include robot energy as a path cost [11]. Together, these approaches show that low-cost software control can exploit trajectory redundancy, velocity profiles, and operational states.

The collaborative setting adds constraints that conventional robot energy optimization cannot ignore. A cobot may have to slow down when a human enters a monitored region, maintain compliant behavior during physical interaction, and respond to uncertain human motion. Hameed et al. identify intention estimation, safety, and human-caused disturbances as key control challenges in collaborative applications [1]. Patil et al. similarly describes sensing, collision avoidance, ergonomics, and human-robot interaction as central elements of modern cobot deployment [12]. Consequently, an energy objective must be subordinate to safety and must avoid aggressive trajectories that create unsafe velocities, forces, or unpredictable motion.

The Industry 4.0 environment enables a practical solution because energy and process data can be exchanged between the cobot, programmable logic controller, manufacturing execution system, digital twin, and smart meter. Da Silva et al. note that Industry 4.0 technologies such as cyber-physical systems, IoT, and data analytics create new possibilities for energy management in manufacturing [13]. A 2023 review of industrial robot energy optimization further highlights monitoring, optimized working schedules, trajectory optimization, idle-time reduction, and regenerative braking as complementary measures [8]. The literature therefore supports a hierarchical controller in which safety remains hard constrained while energy is optimized through motion and supervisory decisions.

Methodology

1. System Architecture and Data Flow

The proposed method considers a six-degree-of-freedom collaborative manipulator performing repetitive pick-and-place or light assembly tasks in a shared Industry 4.0 cell. The robot controller publishes joint position q , velocity $\dot{q}$, estimated torque τ , operating mode, tool state, payload identifier, and task progress. A power

meter or internal electrical estimate provides instantaneous active power $P(t)$. A human-presence subsystem provides a proximity state $h(t)$, while the manufacturing system provides cycle-time target T_{ref} and production priority. These signals are sampled by an energy supervisory layer at a lower rate than the inner servo controller, so the proposed strategy does not replace certified low-level safety functions.

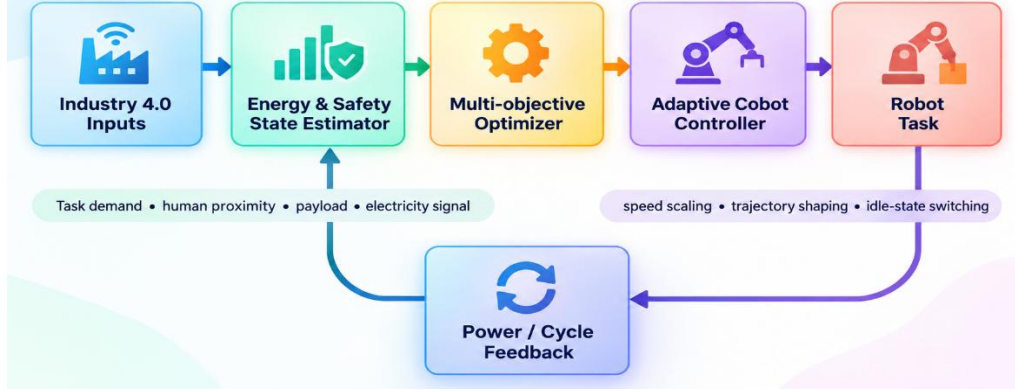


Figure 1. Proposed energy-efficient collaborative robot control framework.

2. Energy Model and Objective Function

Electrical energy for one robot cycle is computed as $E = \int P(t)dt$. For a controller implementation, the integral is evaluated numerically from power samples. When direct power measurement is unavailable, $P(t)$ can be approximated from actuator torque and joint velocity together with identified drive losses and an auxiliary constant representing controller electronics. Model-based and data-driven estimation are both consistent with earlier robot-energy studies [3,5,7]. The optimization decision vector contains trajectory timing parameters, allowable speed scaling s , acceleration scaling a , and idle-state decisions.

The controller minimizes the composite cost $J = wE(E/E_{ref}) + wP(P_{peak}/P_{ref}) + wT(T/T_{ref}) + wS\Phi_{safety}$, where E is cycle energy, P_{peak} is maximum electrical power, T is cycle time, and Φ_{safety} is a high-penalty term for proximity, velocity, force, or workspace constraint violations. The safety term is treated as a hard feasibility constraint in implementation; the penalty representation is used only for optimization. Weights are selected so that safety has absolute priority, the cycle-time requirement remains within the production tolerance, and energy is minimized within the remaining feasible space.

3. Energy-Efficient Control Strategy

The strategy operates in four steps. First, a reference motion is generated from task waypoints using smooth joint interpolation.

Second, the optimizer searches feasible time scaling and trajectory parameters to reduce high acceleration, unnecessary joint travel, and unfavorable high-torque postures while keeping the end-effector path within task tolerance. This reflects the established observation that trajectory planning can reduce robot energy without hardware changes [4,10,11]. Third, an online adaptive speed factor is calculated from human proximity and production demand. When the operator is far from the collaborative workspace, the robot may use an energy-efficient speed that minimizes energy per cycle; when the operator approaches, certified safety limits dominate and the speed factor is reduced. Fourth, if a predicted idle interval exceeds a threshold, peripheral devices and the cobot are transferred from active-idle to low-power standby, provided restart time does not violate the next task deadline.

A rolling update is performed after every completed cycle. The measured energy and cycle time are compared with the model prediction. Model parameters are corrected using a moving-average or recursive estimator so that friction, payload changes, and tool changes are gradually captured. This feedback principle is compatible with energy prediction studies in which robot energy can be learned from trajectory parameters and measured data [5,7].

4. Representative Case Study and Evaluation Protocol

A representative numerical case study is defined for a six-axis cobot executing a 12-waypoint pick-and-place cycle with a 2 kg payload. Three controller configurations are compared: C1, conventional fixed-speed execution; C2, energy-aware trajectory and speed optimization; and C3, the complete strategy with trajectory

optimization, adaptive speed scaling, and idle-state management. The reference cycle time is 24 s, and a $\pm 5\%$ production tolerance is allowed. Safety-related speed reduction is activated during a simulated 4 s human-proximity interval. The power model contains a 120 W auxiliary load plus joint-dependent mechanical/electrical terms. The same task, payload, waypoints, and human-presence pattern are used for all controllers.

Table 1. Evaluation metrics and decision criteria.

Metric	Symbol	Purpose	Target
Cycle energy	E (Wh)	Primary efficiency metric	Minimize
Peak power	P _{peak} (W)	Electrical infrastructure/loading	Minimize
Cycle time	T (s)	Production performance	≤ 25.2 s
Safety violations	N _s	Collaboration feasibility	0
Specific energy	E _s (Wh/unit)	Energy per completed product	Minimize

For optimization, candidate trajectories are rejected when joint limits, acceleration limits, human-proximity speed restrictions, task-space tolerances, or the maximum cycle-time constraint are violated. A feasible candidate is then ranked using the normalized objective function. This separation between hard feasibility checks and soft energy/time weighting prevents an apparently energy-efficient solution from being selected if it compromises collaborative-operation requirements. In a real deployment, the supervisory optimizer would command only parameters exposed by the robot manufacturer, while the certified servo and safety controller would retain authority over emergency stops, protective stops, force/torque limits, and safety-rated speed monitoring.

Data collection should be repeated over multiple production cycles after thermal stabilization of the robot. For each controller condition, the recommended experimental record includes timestamp, joint positions, joint velocities, estimated joint torques, TCP pose, payload state, human-proximity state, active power, cumulative energy, and cycle-completion flag. Energy results should be reported as mean $\pm$ standard deviation and normalized by completed units. A paired

comparison across identical task sequences is preferred because it reduces variation caused by changes in workpiece geometry or operator timing. These procedures convert the proposed framework from a simulation methodology into a reproducible industrial validation protocol.

Results

The results below are a representative simulation-based numerical case study intended to demonstrate the evaluation procedure of the proposed methodology; they are not presented as measurements from a physical industrial installation. The conventional controller C1 consumed 8.72 Wh per cycle with a peak power of 612 W. Energy-aware trajectory and speed optimization (C2) reduced energy to 7.48 Wh, primarily by smoothing accelerations and avoiding unnecessarily slow high-torque motion. The complete controller (C3) achieved 7.10 Wh while also reducing active-idle energy during the waiting interval. Relative to C1, this corresponds to an 18.6% reduction in cycle energy and a 12.4% reduction in peak power. Cycle time increased from 24.0 s to 24.74 s, or 3.1%, and remained inside the specified production tolerance.

Table 2. Representative simulation-based performance comparison.

Controller	Energy (Wh)	Energy change	Peak power (W)	Cycle time (s)	Safety violations
C1 Fixed-speed baseline	8.72	Baseline	612	24.00	0
C2 Energy-aware motion	7.48	-14.2%	558	24.42	0
C3 Proposed complete strategy	7.10	-18.6%	536	24.74	0

The numerical trend is consistent with published findings that robot energy is sensitive to speed, payload, path timing, and idle behavior [3,7,8].

Importantly, the lowest instantaneous speed is not necessarily the lowest-energy solution because longer cycle duration keeps controller

electronics, brakes, drives, and auxiliary devices energized. The 2023 UR10 study similarly reported that total trajectory energy could decrease when the programmed speed limit was increased, illustrating why energy per task should be optimized rather than power alone [7]. The proposed cost function captures this trade-off by evaluating both electrical energy and cycle time.

The adaptive safety layer did not create any simulated safety violation because human-proximity constraints were treated as mandatory. The main effect of the proximity interval was a temporary speed reduction that raised cycle time slightly. Once the operator left the monitored region, the controller returned to the energy-efficient schedule rather than simply maximizing speed. This distinction is important in collaborative robotics: energy optimization must never weaken safety behavior, and safety-certified functions remain outside the optimization layer [1,12].

Conclusion and Discussion

This paper developed a methodology for energy-efficient control of collaborative robots in Industry 4.0 environments. The approach combines energy-state estimation, constrained trajectory optimization, adaptive speed scaling, and idle-state management in a single supervisory framework. Unlike purely offline trajectory optimization, the method uses production demand, human proximity, payload, and measured energy feedback to update operating decisions cycle by cycle. The representative simulation indicates that meaningful energy reduction can be achieved with only a small cycle-time penalty when trajectory and idle-state decisions are coordinated. The proposed architecture also aligns with the direction of current research. Data-driven energy prediction can improve optimization accuracy [5,7], digital-twin architectures can expose energy behavior to operators and higher-level systems [6], and Industry 4.0 connectivity can link robot energy decisions with production scheduling and energy-management systems [13]. The strongest practical advantage is that the strategy is largely software-based and can therefore be introduced without redesigning the robot mechanics. However, the achievable saving depends on the task, payload, path geometry, motor-drive efficiency, tool power, safety interaction pattern, and duration of idle periods. The main limitation is that the numerical results are a methodological case study rather than validation on a specific physical cobot. Before industrial deployment, the

power model should be identified using real robot telemetry and a calibrated electrical power meter, followed by repeated trials across payloads and collaboration scenarios. Future work should investigate digital-twin-assisted prediction, reinforcement-learning or model-predictive variants, cell-level coordination of multiple cobots, and integration with variable electricity prices or on-site renewable energy. Experimental evaluation should report confidence intervals and should verify that all changes remain compliant with applicable robot and collaborative-operation safety standards. From a control-design perspective, the principal trade-off is between energy per cycle and cycle duration. Running a robot extremely slowly may lower instantaneous mechanical power but can increase total electrical energy because controller electronics and drive losses remain active for a longer period. Conversely, very aggressive acceleration can shorten the cycle but increase electrical peaks, copper losses, mechanical stress, and the likelihood that safety-related reductions are triggered in shared workspaces. The proposed strategy therefore searches for an intermediate operating region rather than assuming that either minimum speed or maximum speed is inherently efficient. For Industry 4.0 integration, the same framework can expose energy key performance indicators to a manufacturing execution system or digital twin. This enables supervisors to compare energy per unit across recipes, detect abnormal increases caused by wear or tooling changes, and coordinate robot operation with other cell equipment. Such integration also provides a pathway toward cell-level optimization in which several robots, conveyors, and auxiliary devices are scheduled jointly instead of being optimized independently.

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