Adaptive Control of Robotic Winding Processes Under Variable Material and Environmental Conditions

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Abstract

Robotic winding of continuous fiber composites must maintain fiber tension, orientation, and compaction while material viscoelasticity, spool friction, mandrel geometry, and ambient conditions vary. Fixed-gain controllers tuned to nominal conditions can produce tension drift, fiber slippage, overlap, and void formation when the process departs from its calibration point. This paper develops an adaptive control framework for robotic winding that couples a reduced-order winding and tension model with online parameter estimation, disturbance compensation, and constraint-aware reference adaptation. The model represents winding angle through mandrel radius and axial velocity, tension evolution through supply-deposition velocity mismatch and span compliance, and material behavior through a rate-dependent constitutive relation with time-varying stiffness and damping. Adaptive laws update stiffness, damping, and friction parameters from measurable tension error using projection bounds. A disturbance observer estimates unmodeled spool, guide, and contact effects, while a reference governor adjusts tension and traverse speed when estimated states approach deposition-quality limits. Lyapunov analysis yields sufficient conditions for bounded tracking under bounded parameter variation, and sensitivity arguments identify when estimation excitation is insufficient. The framework makes controller design explicit about sensing, calibration, and failure modes such as tension loss, over-tension, slip, and path deviation. Practical implications include structured fusion of tension and position measurements, separation of slowly varying material properties from fast disturbances, and constraint-aware adaptation for variable material and environmental conditions.

Keywords

robotic filament winding; adaptive control; tension regulation; parameter estimation; disturbance observer; composite manufacturing

1. Introduction

Robotic winding of continuous fiber tows onto mandrels, frames, and customizable formwork is a manufacturing process in which geometric path planning and material-state regulation are tightly coupled. The deposited fiber must follow a prescribed angle, remain under controlled tension, and maintain adequate compaction against the substrate; otherwise, the laminate can develop gaps, overlaps, voids, fiber waviness, or premature damage. Composite manufacturing practice therefore treats tension, speed, and winding angle as primary quality variables rather than secondary machine settings [1]. Industrial robots add flexibility because the deposition point can be controlled in several degrees of freedom, but this flexibility also introduces kinematic redundancy, tool-center-point errors, and dynamic coupling between the robot, the feed system, and the mandrel drive [2]. The resulting control

problem is not simply position tracking. It is the regulation of a material state under changing geometry and changing material behavior.

Adaptive control is a natural candidate because the dominant uncertainties are parametric and slowly varying. Stiffness and damping of the fiber train depend on tow composition, sizing, temperature, and moisture; friction in guides and spool packs changes with wear and accumulation; and the effective mandrel radius changes as layers are deposited. Classical adaptive control provides parameter adjustment and closed-loop stability under structured uncertainty [3], while robust adaptive methods address bounded disturbances, unmodeled dynamics, and parameter drift [4]. Nonlinear adaptive design extends these ideas to systems in which the regressor depends on measured states and the control law must respect actuator and state constraints [5]. The winding process, however, has features that are not fully captured by general robot control alone. The robot manipulator model [6] describes motion, but the fiber tension is governed by the feed train and the deposition contact. Disturbance-observer techniques are useful for the fast, unmodeled components of spool and guide friction [7], and iterative learning can exploit repeatability when the same path is executed repeatedly [8]. Tension itself has a direct influence on composite physical and mechanical properties [9], so tension error is not a benign tracking residual; it is a quality-relevant state.

Robotic winding has also been extended beyond conventional cylindrical mandrels to additive fabrication of large-scale customizable formwork by fiber-reinforced polymer winding [10]. Such applications intensify the control problem because the deposition surface evolves during fabrication, the path may include freeform or open geometries, and the material response can change over a single build. The knowledge gap addressed here is the absence of a coherent control formulation that treats winding angle, tension, material parameter variation, and environmental disturbance within one bounded adaptive architecture while preserving explicit quality constraints. The contribution is a methodological framework consisting of a reduced-order process model, a projection-based adaptive tension controller, a disturbance observer for fast feed-train effects, and a constraint-aware reference strategy for tension and traverse speed. The framework is analytical rather than an empirical validation study; it develops the governing relationships, the control logic, and the stability and sensitivity conditions that any implementation must satisfy.

2. Process Modeling Under Variable Conditions

2.1 Winding kinematics and deposition geometry

The winding angle is determined by the ratio of circumferential velocity at the deposition radius to axial traverse velocity. Let R(t) denote the effective mandrel radius at the contact point, θ(t) the mandrel rotation angle, and x(t) the axial carriage position. Under a no-slip assumption and with the fiber tangent to the deposition surface, the local winding angle satisfies the kinematic relation

$$\beta(t) = arctan(R(t)\theta(t)/\dot{x}(t))$$

where β(t) is the angle between the deposited fiber and the mandrel axis, θ̇(t) is the mandrel angular velocity, and ẋ(t) is the axial traverse velocity. The relation shows that a constant robot program does not produce a constant winding angle when R(t) changes through layer build-up or when the deposition point moves onto a noncylindrical form. Small radius errors are amplified when ẋ(t) is small, so the angle sensitivity is highest during slow traverse segments. The controller therefore requires an estimate of R(t) and of the contact-point position rather than a fixed geometric model.

The effective radius and contact state are not directly measured at every point. Encoders provide θ and x, load cells provide tension, and vision or laser profilometry can provide local surface height; these heterogeneous measurements must be fused with latency and dropout handling [11]. The kinematic relation also exposes a boundary condition for the control model: if the tow slips on the mandrel, the no-slip assumption fails, and β(t) is no longer determined solely by commanded velocities. Slip detection must therefore be treated as a mode change rather than a parameter perturbation. Similarly, if compaction pressure is too low, the deposited fiber may not remain on the intended geodesic path even when the robot pose is correct. The model is thus a control-oriented representation of the deposition geometry, not a complete contact-mechanics model.

2.2 Tension, material variability, and environmental disturbance

The tension in the free span between the feed rolls and the deposition point can be represented by a lumped balance between supply velocity, deposition velocity, span compliance, damping, and external disturbance. A control-oriented form is

$$T = (EA/\ell)(v_s - v_d) - (c/\ell)T + d_T$$

where T is the fiber tension, E is the effective fiber modulus, A is the tow cross-sectional area, ℓ is the free-span length, v_s is the supply velocity, v_d is the deposition velocity, c is a damping coefficient, and d_T collects spool-pack friction, guide drag, and unmodeled contact effects. The term (EA/ℓ)(v_s−v_d) represents the elastic buildup or release of tension caused by velocity mismatch, while −(c/ℓ)T represents dissipation in the span. The disturbance term is not assumed to be constant; it may vary with spool radius, guide wear, and tow path curvature. This model is deliberately low order because the controller must operate at the deposition bandwidth and because higher-order phenomena such as tow bending stiffness are better handled as bounded uncertainty or through the disturbance observer.

Material variability enters the model through the constitutive behavior of the tow. For small strain and approximately uniform tension over the free span, a rate-dependent representation is

$$T = E(t)A\varepsilon + \eta(t)A\dot{\varepsilon}$$

where ε is the axial fiber strain, $\dot{\varepsilon}$ is its time derivative, E(t) is the time-varying effective modulus, and η(t) is a time-varying viscoelastic coefficient. The first term captures elastic tension, and the second captures rate-dependent resistance associated with sizing, resin tack, and fiber friction. The separation is useful because E(t) and η(t) evolve slowly with temperature, moisture, and material lot, whereas d_T can change quickly with spool rotation and guide contact. Online identification of E(t), c, and η(t) can be performed with recursive least squares or a constrained parameter estimator using measured tension and velocity [12]. The estimator must include forgetting or covariance reset logic because a constant-speed segment may provide insufficient excitation to distinguish stiffness from friction. The model assumes that the tow remains continuous and engaged with the feed rolls; if the tow breaks or the feed rolls lose grip, the tension dynamics change qualitatively.

3. Adaptive Control Architecture

3.1 Parameter adaptation and robust compensation

The control objective is to track a tension reference T_ref(t) while maintaining the winding angle within a quality envelope and respecting actuator limits. Let e_T(t)=T_ref(t)−T(t) denote the tension tracking error. The command to the feed motor is

composed of a feedforward term based on estimated parameters, a proportional-derivative feedback term, and a disturbance compensation term:

$$u = u_ff(\theta) + K_p\, e_T + K_d\, \dot{e}_T - \hat{d}_T$$

where u is the motor command, u_ff(θ̂) is the feedforward velocity or torque command computed from the current parameter estimate θ̂, K_p and K_d are positive feedback gains, and d̂_T is the estimated disturbance. The feedforward term reduces the burden on feedback when the tow modulus or span length changes, while the derivative term adds damping against tension oscillations. The disturbance term prevents the feedback gains from having to be raised solely to reject spool and guide effects.

The parameter estimate is updated from the tension error and a regressor constructed from measured velocity and tension states:

$$\dot{\theta} = Proj_\Theta(\Gamma\, \varphi\, e_T)$$

where θ̂ is the vector of estimated parameters such as EA, c, and ηA, φ is the regressor derived from the tension-error model, Γ is a positive-definite adaptation gain matrix, and Proj_Θ denotes projection onto a bounded parameter set. Projection is important because unconstrained adaptation can drift when the reference is constant or when disturbances are correlated with the regressor. The bounded set Θ should be derived from material specifications and calibration data, not chosen arbitrarily. Lyapunov synthesis provides the stability rationale for combining the adaptation law with the damping term [13]. The adaptation gain determines the speed of parameter correction, but high gain also transfers sensor noise into the command. The design trade-off is therefore not merely convergence speed; it is the separation of true parameter variation from measurement noise and unmodeled high-frequency dynamics.

3.2 Disturbance estimation and constraint-aware reference adaptation

Fast disturbances are handled by an observer rather than by the parameter update. Let z be the observer state and K_o a positive observer gain. A reduced-order observer update can be written as

$$\dot{z} = -K_o\left(z + K_o T + \left(\hat{E}\frac{A}{\ell}\right)(v_s - v_d) - \left(\frac{\hat{c}}{\ell}\right)T\right)$$

with the disturbance estimate defined by d̂_T=z+K_o T, where ÊA and ĉ are the current parameter estimates. The observer estimates the low-frequency image of unmodeled spool and guide effects without requiring a detailed friction model. Its bandwidth must be slower than the dominant sensor noise but faster than the spool rotation disturbance; if the observer is too fast, it will absorb measurement noise and produce command chatter. This separation of time scales is the central reason for combining adaptation with a disturbance observer instead of relying on one mechanism alone. Parameter adaptation addresses persistent material changes, while the observer addresses fast exogenous loading.

The reference itself must be adjusted when quality constraints approach their limits. A constraint-aware governor can modify T_ref and the traverse-speed command within admissible sets defined by minimum tension for slip avoidance, maximum tension for fiber damage, and maximum angle deviation for coverage. Model predictive control provides a structured way to compute such constrained references using a process model and a receding horizon [14]. In the winding context, a full predictive controller may be unnecessary, but the reference governor should still enforce the admissible set explicitly. For example, if the

estimated radius increases suddenly, the kinematic relation implies a change in β for constant velocities; the governor can reduce traverse speed before the angle limit is violated. If the estimated disturbance indicates a spool friction increase, tension may be maintained by feedforward compensation, but the maximum tension constraint must remain active. The governor thus converts adaptation from an unconstrained tracking exercise into a quality-preserving decision rule.

4. Stability and Sensitivity Analysis

Stability can be assessed with a Lyapunov function containing the tension error and parameter error. Let $\tilde{\theta}=\theta-\theta^{*}$ and consider

$$\dot{V} \leq -\lambda_{min}(K_d)e_T^2 + \kappa|e_T|\bar{d}$$

where V is a positive-definite function of e_T and $\tilde{\theta}$, $\lambda_{min}(K_d)$ is the minimum eigenvalue of the damping gain matrix, κ is a bounded constant depending on the regressor and projection set, and $\bar{d}$ is the disturbance bound. Under projection, bounded reference variation, and bounded disturbance, the derivative condition implies ultimate boundedness of the tension error rather than asymptotic convergence to zero. This distinction matters in winding: the goal is not zero error under all conditions but an error that remains within the quality envelope while parameters change. If the disturbance bound grows, the ultimate bound grows unless the damping gain or observer bandwidth is increased; both actions have noise and actuator costs. The inequality therefore provides a design constraint rather than a performance guarantee.

Parameter identifiability depends on excitation. If the process runs at nearly constant velocity and tension, the regressor may be persistently non-exciting, and the estimates of stiffness, damping, and friction may not be distinguishable. In that case, the adaptation should be slowed or suspended while the disturbance observer and robust feedback maintain regulation. A persistent-excitation condition requires the regressor outer product to remain positive definite over a moving time window of sufficient length, but the window cannot be so long that it averages away real material transitions. The practical consequence is that adaptation should be event-aware: a change in spool radius, a new material lot, or a measured environmental shift can justify temporary gain adjustment or a deliberate change in traverse speed to restore observability.

Sensitivity analysis connects model errors to quality outcomes. The winding angle is most sensitive to radius error when the axial velocity is small; the tension is most sensitive to velocity mismatch when the span is short and the tow stiffness is high. Material variability alters both the elastic and dissipative terms in the constitutive relation, so a controller tuned only to nominal stiffness can misinterpret a damping change as a feed-drive disturbance. Composite design practice recognizes that fiber architecture and processing history affect stiffness, strength, and damage tolerance [15], and delamination and void formation are especially sensitive to local consolidation and fiber movement [16]. These effects do not require the controller to model damage mechanics directly. They require the controller to keep tension and angle inside ranges where such mechanisms are not activated. Sensitivity analysis thus translates model uncertainty into admissible operating margins.

5. Implementation and Technical Discussion

5.1 Sensor and calibration logic

A practical adaptive winding controller needs three measurement classes: kinematic measurements from robot and mandrel encoders, tension measurements from in-line load cells or torque observers, and environmental measurements from temperature and humidity sensors near the feed path. The kinematic measurements are used in the winding-angle relation and in the radius estimate. The tension measurement is used for feedback and parameter adaptation. The environmental measurements are used to schedule parameter bounds or to adjust the reference governor because thermal and hygrothermal effects can change fiber sizing, resin tack, and friction [17]. Calibration must separate sensor offset from process offset. A load-cell zero offset is not the same as a feed-train friction bias; if the two are conflated, the adaptive law will learn a false material parameter. A practical sequence is to calibrate the load cell unloaded, estimate guide friction over a slow forward and reverse feed without deposition, and then identify the span compliance with a known tow. The projection set Θ should be initialized from these offline estimates and updated only within physically plausible limits.

The fusion problem is not merely averaging. Encoder measurements are high-rate but do not observe surface height directly; vision measurements are spatially informative but delayed; tension measurements are high-rate but integrate friction and material effects. A fusion layer should therefore propagate uncertainty and reject outliers before the estimates enter the adaptation law [11]. If the radius estimate is lost, the controller should fall back to the last bounded estimate and reduce adaptation gain rather than extrapolate indefinitely. If the tension signal saturates, the controller should switch to a safe tension-hold mode and inhibit parameter updates. These logic choices are part of the control design, not implementation details, because they determine whether the stability assumptions remain valid during faults.

5.2 Failure modes and design trade-offs

The dominant failure modes are tension loss, over-tension, slip, path deviation, and parameter drift. Tension loss is often caused by spool-pack friction or loss of feed-roll grip; it appears as a rapid drop in measured tension and a mismatch between commanded and actual deposition velocity. Over-tension can arise from aggressive disturbance compensation or from a reference governor that demands tension beyond the fiber or guide limit. Slip invalidates the kinematic angle relation and can produce local overlap even when the tension is nominal. Parameter drift is more subtle: an adaptation law can absorb a slowly changing sensor bias and then command an incorrect feedforward during a material transition. Projection bounds, observer separation, and explicit constraint checks reduce these risks, but they do not eliminate them.

The principal design trade-offs follow from these failure modes. Increasing adaptation gain improves response to material change but increases noise sensitivity and the risk of parameter drift. Increasing observer bandwidth improves disturbance rejection but can destabilize the feed loop when actuator delay or sensor filtering is significant. Increasing tension improves compaction and reduces slack, but it raises fiber damage and guide wear. Reducing traverse speed improves angle resolution and excitation for identification, but it reduces productivity and can alter the thermal history of the deposited material. A digital process model can help manage these trade-offs by maintaining calibrated parameter bounds, documenting material lots, and simulating constraint margins before a path is executed [18]. Such a model does not replace closed-loop control; it supplies the controller with context that the feedback loop cannot infer from tension alone.

6. Conclusion

Robotic winding under variable material and environmental conditions requires more than a fixed tension gain and a precomputed robot path. The angle of deposition depends on an evolving radius and velocity ratio, the tension depends on feed-train dynamics and material viscoelasticity, and the dominant uncertainties separate into slow parameter changes and fast disturbances. The adaptive framework developed here addresses that structure directly. A kinematic winding relation defines the angle constraint, a reduced-order tension model defines the controllable dynamics, and a rate-dependent constitutive relation represents material variability. Projection-based parameter adaptation updates stiffness, damping, and friction estimates; a disturbance observer compensates spool and guide effects; and a constraint-aware reference governor keeps tension and traverse speed within quality limits. Lyapunov and sensitivity arguments provide sufficient conditions for bounded tracking and identify when insufficient excitation or rapid parameter change limits identifiability. The practical contribution is a design logic for sensing, calibration, fault handling, and trade-off selection that is specific to robotic winding rather than inherited from generic manipulator control. The framework is analytically grounded and implementation-ready in structure, although its quantitative parameter bounds must be established from material characterization and process calibration.

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