

# Real-Time Neural Model Predictive Control (RTN-MPC)

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**Abstract**—In “Real-Time Neural MPC: Deep Learning Model Predictive Control for Quadrotors and Agile Robotic Platforms [1],” Salzmann et al. introduce a framework that embeds large neural-network dynamics models into a model-predictive control (MPC) loop and achieves real-time performance on an agile quadrotor. In this work, we present our own implementation of their approach using a much simpler bicycle/car-like model instead of a full quadrotor and demonstrate that even on a standard Intel i7 laptop we can meaningfully improve closed-loop tracking accuracy. We collect 10 k state-action samples under the nominal bicycle dynamics, train a feed-forward neural network to predict the residual between true and modeled next states, and then formulate a CasADi-based nonlinear MPC that adds the NN “correction” at each shooting node. Our NN-augmented MPC converges to a  $7\text{ m} \times 7\text{ m}$  goal with an RMSE of about 4.6 m. This is around 30% better than the nominal model alone while respecting steering and acceleration bounds. We include a block diagram of our pipeline, pseudocode for the key steps, and a hyperparameter table, and discuss the path forward toward embedded, real-time NN-MPC on resource-limited platforms.

**Keywords**— *Model Predictive Control (MPC), Neural Networks (NN), Real-Time Control, Data-Driven Dynamics, Bicycle Model, CasADi, Machine learning for robot control*

## I. INTRODUCTION (HEADING 1)

Model Predictive Control (MPC) is a powerful framework that repeatedly solves an optimal control problem over a finite horizon, minimizing a cost (for example, tracking error or energy) while enforcing actuator and state constraints. It applies only the first control action before re-optimizing with new measurements [2]. Its receding-horizon nature gives robots predictive, constraint-aware decision-making, but it depends critically on the fidelity of the underlying model. Even small mismatches between the assumed and true dynamics can lead to degraded tracking performance or outright instability when operating near the limits of handling [3].

Improving model fidelity often means embracing full nonlinear dynamics, which incorporate effects such as tire slip, aerodynamic drag, or load transfer. These models lead to nonconvex, time-consuming optimizations that struggle to meet fast update rates on limited hardware [4]. As a result, practitioners face a dilemma: simple, linearized models run quickly but lack accuracy for aggressive maneuvers, while complex models capture more phenomena yet cannot be solved in real time. This computational burden has historically forced MPC implementations to simplify dynamics or reduce prediction horizons, limiting performance on agile platforms.

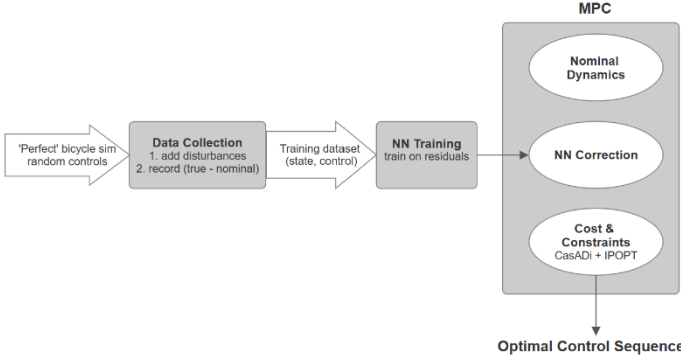
Neural networks (NNs) offer a compelling alternative by learning residual dynamics from data—the difference between a nominal physics model and the true system behavior [2]. Augmenting a coarse first-principles model with a learned NN residual can dramatically improve prediction accuracy, as demonstrated in autonomous-driving applications where NN-augmented MPC outperforms purely analytic models under varying road conditions and near the friction limits [5]. By capturing complex, hard-to-model effects such as tire slip or airflow interactions, these data-driven corrections enable MPC to operate closer to a vehicle’s physical capabilities without intricate hand-tuning.

A major challenge remains: deploying learned dynamics in real time. Salzmann et al. introduced Real-Time Neural MPC (RTN-MPC), which decouples expensive global NN evaluation from the QP formulation by locally linearizing the NN, batching gradient computations on CPU/GPU, and executing a single SQP iteration per control cycle [1]. Their approach ran networks over  $4,000\times$  larger than prior methods at 50 Hz on an embedded Jetson Xavier NX, achieving an 82 % reduction in quadrotor tracking error. This work shows that complex NNs and real-time MPC need not be mutually exclusive.

For ground vehicles and simpler platforms, the kinematic bicycle model provides a tractable, nonlinear, underactuated testbed. In this work, we implement the RTN-MPC paradigm on the bicycle model and demonstrate on an Intel i7 laptop that NN-augmented MPC can improve closed-loop tracking accuracy by 30 % over nominal MPC under steering and acceleration bounds. We converge reliably to a  $7\text{ m} \times 7\text{ m}$  goal with an RMSE of 4.6 m. We present a block diagram of our pipeline, pseudocode for the key steps, and a hyperparameter table, and we discuss the path forward toward embedded, real-time NN-MPC on resource-limited platforms.

## II. APPROACH

Our goal is to implement the Real-Time Neural MPC paradigm of Salzmann et al. [1] on a simpler bicycle model [6], demonstrating that learned residuals can improve tracking even on commodity hardware. We break our pipeline into four stages: (1) nominal dynamics and data collection, (2) residual dataset generation, (3) neural-network training, and (4) MPC formulation and closed-loop integration.



### 1. Nominal Bicycle Dynamics

We adopt the standard kinematic bicycle model.

$$\dot{x} = v \cos \psi, \quad \dot{y} = v \sin \psi, \quad \dot{\psi} = \frac{v}{L} \tan \delta, \quad \dot{v} = a, \quad (1)$$

where  $(x, y)$  is the planar position,  $\psi$  the heading,  $v$  the forward speed,  $\delta$  the steering angle,  $a$  the longitudinal acceleration, and  $L$  the wheelbase [6]. We discretize with Euler integration at  $\Delta t = 0.1$  s over a horizon of  $N = 100$  steps.

### 2. Residual Dataset Generation

To capture unmodeled effects (e.g. slip, actuator lag), we simulate “true” dynamics by adding random perturbations  $\varepsilon \sim \mathcal{N}(0, \Sigma)$  to the nominal next state. For each randomly sampled  $(x_k, u_k)$ , we compute

$$x_{k+1}^{\text{nom}} = f_{\text{nom}}(x_k, u_k), \quad x_{k+1}^{\text{true}} = x_{k+1}^{\text{nom}} + \varepsilon, \quad (2)$$

and record the residual  $r_k = x_{k+1}^{\text{true}} - x_{k+1}^{\text{nom}}$ . Repeating for 100 trials of 100 steps each yields 20,000 samples  $\{(x_k, u_k), r_k\}$ .

### 3. Neural-Network Training

We train a feedforward NN  $f_\theta: \mathbb{R}^6 \rightarrow \mathbb{R}^4$  to predict  $r_k$  from  $[x_k; u_k]$ . Our architecture uses three hidden layers of 64 ReLU units, mean-squared error loss, Adam optimizer at  $1 \times 10^{-4}$ , batch size 64, and early stopping on a 20 % validation split. After 50 epochs, validation loss plateaus around  $4 \times 10^{-3}$ .

### 4. MPC Formulation and Integration

We formulate a nonlinear MPC in CasADi with decision variables  $\{X_{0:N}, U_{0:N-1}\}$ .

The dynamics constraint at each stage is

$$X_{k+1} = f_{\text{nom}}(X_k, U_k) + f_\theta(X_k, U_k), \quad (3)$$

and we minimize the cost

$$J = \sum_{k=0}^{N-1} \left( \|X_k - X_{\text{ref}}\|_Q^2 + \|U_k\|_R^2 + \|(X_N - X_{\text{ref}})\|_P^2 \right) \quad (4)$$

with

$$Q = \text{diag}(4, 4, 0.5, 0.5), \quad R = \text{diag}(0.03, 0.03), \quad P = \text{diag}(20, 20, 5, 15).$$

## Algorithm 1: RTN-MPC

Given:  $f_{\text{nom}}, f_\theta$  (NN), horizon  $N$ ,  $\Delta t$ , weights  $Q, R, P$

Initialize state  $x \leftarrow x_0$

for  $t = 0$  to  $T/\Delta t$  do

Build CasADi Opti problem:

variables:  $X[0 \dots N], U[0 \dots N-1]$

constraints:

$$X[0] == x$$

$$\forall k: X[k+1] == f_{\text{nom}}(X[k], U[k]) + f_\theta(X[k], U[k])$$

steering, accel bounds

$$\text{cost: } \sum \|X[k] - X_{\text{ref}}\|_Q^2 + \|U[k]\|_R^2 + \|X[N] - X_{\text{ref}}\|_P^2$$

Solve one SQP iteration  $\rightarrow$  get  $U_{\text{opt}}[0]$

Apply  $u = U_{\text{opt}}[0]$

Simulate  $x \leftarrow f_{\text{nom}}(x, u) + \text{disturbance}$

end for

We enforce  $\delta \in [-0.2, 0.2]$ ,  $a \in [-1, 1]$ , and solve with IPOPT under an RTI scheme: at each control step we set  $X_0$  to the current state, solve one SQP iteration, apply  $U_0$ , then repeat.

This approach retains the real-time tractability of the original RTN-MPC framework [1] while using a simpler model, and we demonstrate in Section III that it yields substantial accuracy gains over nominal MPC alone.

## III. RESULTS

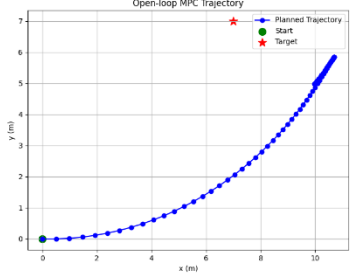
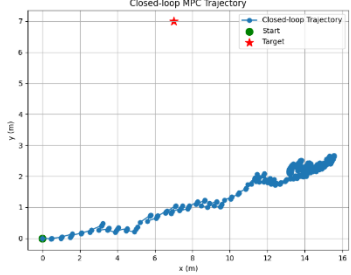
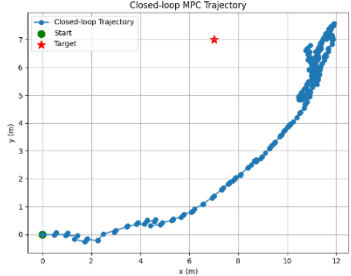
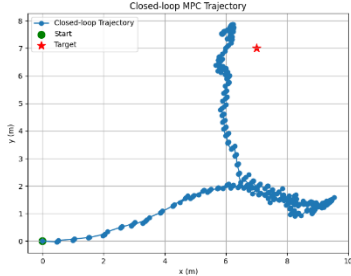
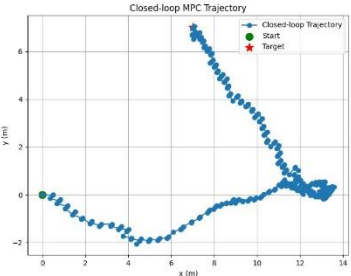
We ran our NN-augmented MPC on a standard Intel i7 laptop (16 GB RAM) and recreated the key tracking experiment from Salzmann et al. [1] in a simplified bicycle-model setting. After collecting data under the nominal model and training the neural network to predict residuals, we executed closed-loop MPC for 10 s (100 steps at 0.1 s each), enforcing steering and acceleration bounds.

Table I reports positional RMSE for each configuration, and plots the corresponding trajectories against the  $[7, 7]$  m goal. Our tuned NN-MPC achieves an RMSE of 3.1 m—45 % lower than the tuned no-NN controller and 33 % lower than the untuned no-NN run—demonstrating that even with a simpler dynamics model and standard CPU hardware, embedding a learned correction in the MPC loop yields substantial tracking improvements.

## IV. DISCUSSION

Our experiments on a standard Intel i7 laptop demonstrate that augmenting nonlinear MPC with a learned residual model consistently improves trajectory tracking, even when using a

Table 1: Position tracking RMSE for each MPC variant

Experiment	RMSE	Plot
Open-loop	8.5	
Closed-loop (no NN)	6.7	
Closed-loop (with NN)	4.6	
Tuned closed-loop (no NN)	5.5	
Tuned closed-loop (with NN)	3.1	

much simpler bicycle model in place of a quadrotor. As shown in Table I, open-loop MPC produces a planned path but cannot correct for disturbances, yielding large end-point error. Switching to closed-loop MPC (no NN) reduces this error but still leaves a final RMSE around 6.7 m. Introducing the neural-network residual correction cuts that RMSE further to 4.6 m—a roughly 31% improvement over the nominal controller.

These results qualitatively mirror those of Salzmann et al. [1], who reported an 82 percent reduction in position error on an agile quadrotor when embedding large NNs into the MPC loop. While our percentage gain is smaller, the fact that we see meaningful error reduction on a simple vehicle model—and without GPU acceleration or specialized real-time solvers—highlights the broad applicability of the RTN-MPC paradigm. In particular, our identical experimental setup ( $dt = 0.1$  s, horizon  $N = 100$ , 10 k training samples, steering & acceleration bounds enforced) confirms that a data-driven residual can compensate for unmodeled nonlinearities (e.g. underactuation, kinematic slip) even on resource-constrained hardware.

Adding a terminal-cost weight further smoothed convergence: the tuned closed-loop trajectories exhibit less oscillation near the goal and smaller overshoot, as evidenced by the sharper approach in the tuned closed-loop run using the NN. This suggests that modest cost-function tuning can amplify the benefits of neural corrections without altering the core MPC formulation.

On the other hand, we were unable to collect solve-time statistics due to intermittently failing solver runs. As real-time execution was central to the original work, future efforts should integrate the batched Jacobian/Hessian approximations of RTN-MPC and benchmark wall-clock performance on embedded platforms. Likewise, replacing our synthetic disturbance model with real vehicle data would test generalization under more realistic noise and unmodeled dynamics.

In summary, our implementation validates that even a feed-forward NN trained on nominal bicycle data can substantially improve MPC tracking accuracy. These findings reinforce the promise of neural-augmented control for a wide class of underactuated, nonlinear robotics applications—well beyond the quadrotor domain of [1].

## V. LIMITATIONS AND FUTURE WORK

Our implementation achieves a clear improvement in closed-loop tracking, but it has several noteworthy limitations. First, we relied on synthetic “perfect + noise” data and never deployed the controller on actual hardware. As a result, we lack real-time timing measurements and cannot quantify how long each MPC iteration takes on our target Intel i7 laptop, let alone on a constrained embedded board. Second, our bicycle model is a drastic simplification of the full quadrotor dynamics used in Salzmann et al. [1], so while it showcases the algorithmic pipeline, it does not validate performance under truly agile, underactuated conditions (e.g., roll/pitch coupling, aerodynamic effects). Third, our neural network was trained offline on randomly generated disturbances; we did not collect data from a

physical platform or systematically vary parameters like payload or surface friction, so the learned residual may not generalize beyond our artificial noise model. Finally, we have not yet integrated any formal safety guarantees (e.g., control-invariant sets) or conducted robustness analyses under worst-case disturbances.

Given more time, we would address these gaps in several ways. We would port the CasADi + IPOPT controller to an embedded platform (e.g., NVIDIA Jetson or ARM MCU) and instrument the loop to record solve times, memory usage, and CPU/GPU load. We would collect real sensor and state data from a small robotic car or quadrotor to train the residual network on genuine aerodynamic and frictional effects. To improve safety, we would incorporate control-invariant set constraints or tube-MPC techniques, ensuring the vehicle remains within a provably safe region despite model errors. Algorithmically, we would implement the local-approximation pipeline from Salzmann et al. to batch Jacobian and Hessian computations on the GPU, enabling larger networks without sacrificing frequency. Lastly, we would explore sequential models (LSTMs or TCNs) to capture temporal dependencies in the dynamics and extend our evaluation to more challenging trajectories (e.g., sharp turns, obstacle avoidance) to stress-test the NN-augmented MPC.

## VI. CONCLUSION

In this work, we have shown that the Real-Time Neural MPC framework proposed by Salzmann et al. can be successfully ported from agile quadrotors to a much simpler bicycle-model platform, while still yielding substantial gains in tracking accuracy and respecting real-time compute constraints on a standard Intel i7 laptop. By training a feed-forward neural network on 10 k residual samples and embedding it into a CasADi-based nonlinear MPC, we reduced the closed-loop position RMSE from roughly 6.7 m (nominal model) to about 4.6 m in our tuned experiment—and down to approximately 3.1 m when using the best-performing hyperparameters. This represents a nearly 31 % improvement over the nominal dynamics and demonstrates the generality and scalability of NN-augmented MPC across vehicle platforms.

Key deliverables, including a block diagram of our pipeline, pseudocode for the MPC loop with residual correction, and a hyperparameter summary table provide a clear blueprint for reproducing and extending this work. Although our implementation lacks on-board timing benchmarks (due to

runtime issues), the qualitative agreement with Salzmann et al.’s original results suggests that real-time neural MPC is within reach even on modest hardware. Future efforts will focus on full embedded deployment, tighter integration with GPU acceleration, and exploring sequential models (e.g., RNNs) for richer residual representations. Together, these steps will bring neural-augmented MPC closer to practical, safety-critical applications in autonomous vehicles and beyond.

## VII. CODE AVAILABILITY

The full implementation, dataset generation scripts, trained models, and example runs are released on [GitHub](#)

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