Comparing Residual and Full Data-Driven Inverse Dynamics Models for an Industrial Delta Robot

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Delta robots are parallel kinematic machines used for fast handling tasks such as pick-and-place. The parallel structure keeps the moving mass low and allows high accelerations, but it also makes the dynamics difficult to model: the inertia at each drive depends on the platform position, the axes are coupled, and friction and the handled payload contribute additional torques. A rigid-body model describes the inertia, Coriolis and gravity terms, but does not always capture friction, payload-dependent effects or deviations in the assumed parameters. These remaining effects can be identified from measurements of the real machine. Identifying the complete dynamics from data instead would discard the physical knowledge that is already available and yield a model that is difficult to verify. This work retains the rigid-body model from [1] and identifies only the unmodeled dynamics, using sparse regression. This residual approach is compared with alternative combinations of regression target and model class.

Joint torques are reconstructed from measured motor currents, and the residual $\Delta\boldsymbol{\tau} = \boldsymbol{\tau}_{\mathrm{meas}} - \boldsymbol{\tau}_{\mathrm{nom}}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})$ is formed using measurement and the nominal rigid-body prediction. By design this residual contains everything the rigid-body model does not explain. It is approximated as a sparse linear combination $\Delta\boldsymbol{\tau} \approx \boldsymbol{\Theta}\boldsymbol{\xi}$ of candidate functions comprising velocity-dependent friction terms (viscous, smoothed Coulomb), configuration-dependent terms for gravity and inertia mismatch, and acceleration-proportional terms for payload and coupling effects, with $\boldsymbol{\xi}$ obtained by sparse regression [2, 3].

To separate the effect of the model formulation from that of the regression method, four models are identified by combining both choices: total torque or residual, and sparse regression or neural network. This gives a full sparse model, a full neural network, a residual neural network, and the residual sparse model. All four are fitted on excitation trajectories, tuned on a common validation set and evaluated on a structurally different, unseen test trajectory.

The residual sparse model achieves the lowest error on the unseen trajectory, reducing torque RMSE by 42% and MAE by 65% relative to the nominal model. More informative than the ranking is the structure of the result: the dominant factor is the regression target rather than the model class, with both residual formulations transferring better than either full-signal model. Retaining the nominal model means the identified part represents only the small, structurally simple remainder, while the nominal dynamics part continues to extrapolate where the learned part does not. The identified sparse residual model uses 34 active terms out of 60 candidates, against 5433 parameters in the residual network, and those terms are directly readable. This enables a direct physical plausibility check that is not available to the same extent for a black box model, and, it means the minimal model is extended rather than replaced. The intended application is model based feedforward compensation through the command channel of the existing control [4]. The closed loop benefit of the presented identification is however yet to be proven.

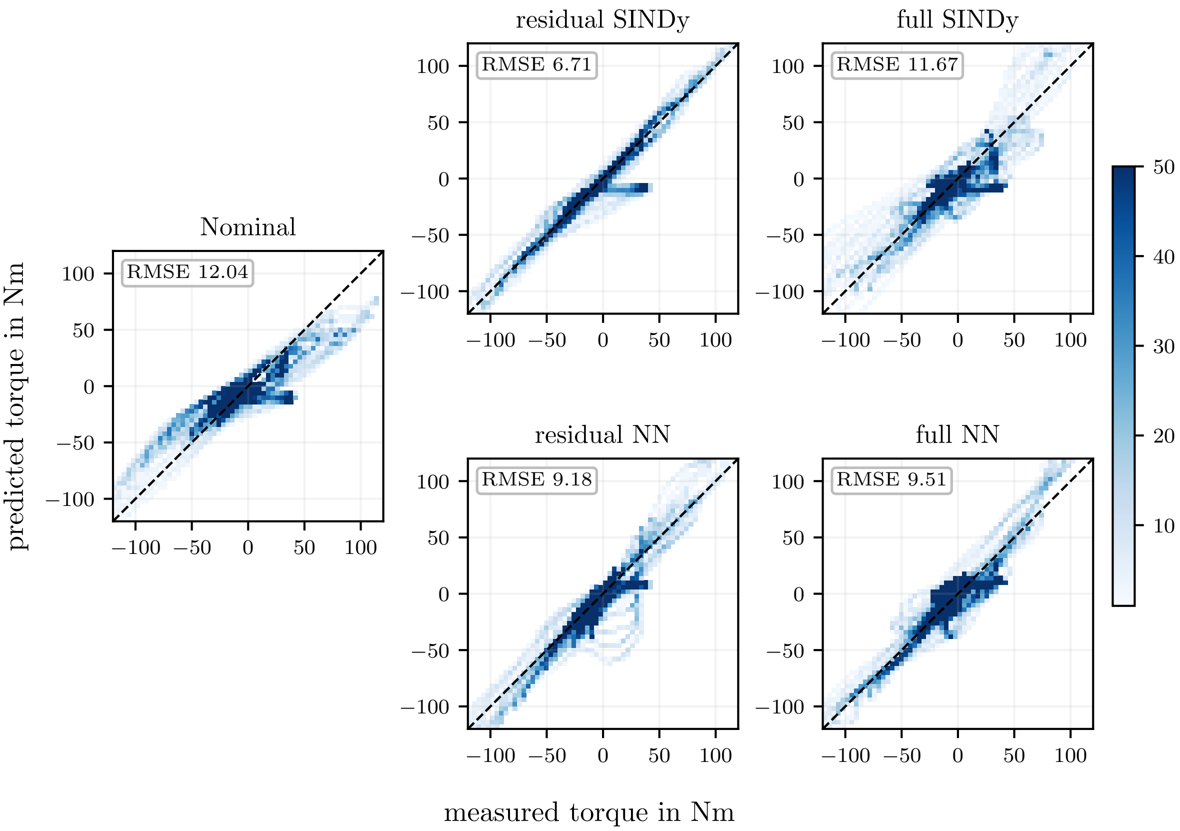

Figure 1: Parity of predicted versus measured joint torque for axis 1 on the held-out test program, with the dashed line indicating ideal agreement and all panels sharing identical binning and density scaling.

References

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