Quantum Reservoir-Based Surrogate Modeling for Large Amplitude Gust Responses of a Two-Dimensional Airfoil

Fabian Fischbach[1], Steffen Leger[1], and Diliana Friedewald[2]

[1]Institute for AI Safety and Security, German Aerospace Center (DLR), St. Augustin & Ulm
[2]Institute of Aeroelasticity, German Aerospace Center (DLR), Göttingen

2nd International Conference on Applied Quantum Methods in Computational Science and Engineering, 14–17 September, TU Delft, The Netherlands

---

1 Problem description and relevance

The design of a transport aircraft requires a large number of load computations for an optimal structural sizing. Different flight points, maneuver and gust load cases, as well as different mass and failure cases, and control laws need to be taken into account, easily summing up to hundreds of thousands of simulations per design cycle. Current simulations are therefore based on unsteady linearized aerodynamic methods [1, 2] as these are computationally efficient. However, when it comes to modern aircraft design, more accurate methods are necessary in order to exploit the full design space and optimize the aircraft's weight. Especially when it comes to large-amplitude excitations as they need to be computed for gust encounters, the currently used time-linearized methods naturally have their limitations. Time-linearized predictions might result, e.g., in an overprediction of actually occurring loads [3] due to an insufficient modeling of, e.g., unsteady flow separation [4]. Therefore, unsteady nonlinear aerodynamic methods, e.g., based on the Unsteady Reynolds-Averaged Navier-Stokes (URANS) equations, are increasingly applied for gust load computations. One of their biggest drawback, however, is the enormous increase in computational time when compared to a RANS-based time-linearized formulation such as, e.g., a time-linearized frequency-domain solver [5].

This work addresses this specific bottleneck by exploiting the advantages of a reservoir computing-based (RC) surrogate approach for the time-domain prediction of URANS-based gust responses: In general, RC [6, 7] leverages a fixed nonlinear dynamical system (the reservoir) to project inputs into a high-dimensional space such that complex nonlinear relationships become easier to represent and extract. Unlike deep neural networks, RC requires training only of the output layer, typically via simple linear regression, mapping the high-dimensional space to the training targets. The training is therefore computationally very efficient and stable. The reservoirs intrinsic dynamics naturally retain memory of past inputs and capture temporal dependencies, making RC particularly suited for modeling dynamical systems and time series data.

Using quantum reservoir computing (QRC) [8] might even enhance the strengths of classical RC: First, quantum systems naturally evolve in high-dimensional Hilbert spaces, so a relatively small number of qubits can generate a rich set of nonlinear transformations, potentially boosting the expressive power of the reservoir without increasing system size in the classical sense. Secondly, quantum dynamics inherently include features such as superposition, entanglement, and

interference. These properties may provide richer temporal and nonlinear processing capabilities than classical reservoirs, potentially improving performance on complex physical systems such as the one described by the current use case.

This leads to the idea of using QRC as a data-driven surrogate to complement costly URANS computations, thus reducing the total computation time while keeping the approximation error acceptable: Use the high-fidelity model only in a subset of the parameter space, and the cheaper surrogate for the rest to balance accuracy and efficiency. This is explored exemplarily for the problem of computing gust responses of a two-dimensional airfoil in terms of two global coefficients across different gust configurations.

2 Methodology

The methodological approach is hybrid quantum-classical in a two-fold sense. First, the training data needed for constructing the surrogate is still generated by classical Computational Fluid Dynamics (CFD) simulations. Second, QRC itself is a hybrid quantum-classical machine learning (ML) approach, meaning that although nonlinear feature generation and memorization of recent inputs are off-loaded to a quantum reservoir, post-processing the reservoir output, in particular the regression, remains classical CPU duty (as does hyperparameter optimization).

Given this categorization, details are as follows. Simulations are carried out using the DLR TAU-Code [9, 10], which is a Finite-Volume-RANS solver. In a time-marching computation, the gust is fed in as external velocity excitation and the response of the airfoil is computed in terms of local pressures, as well as global forces and moment, see [11]. Here the so-called RAE2822 [12] is considered, a two-dimensional airfoil well-known in the aerodynamic community that shows flow features comparable to airfoils from transonic transport aircraft configurations.

These simulations provide multivariate time series data (gust velocity and resulting lift and pitching coefficients) for different shapes of the exciting gust, e.g., for sinusoidal gusts of different amplitudes and period lengths. The flight point is kept fixed. The core supervised learning task then consists in predicting the value of the two coefficients in the next time step when given their current value as well as the current value of the exciting gust velocity as input.

Adapting parameter-aware RC [13, 14, 15, 16] to QRC, a QRC trained on time series associated with a subset of all gust configurations — belonging to a fixed gust length but varying amplitudes (or vice versa) — is able to accurately predict the evolution of the resulting coefficients when driven with unseen gust configurations.

In the literature several recurrent schemes have been proposed under the umbrella of QRC, differing in particular in how and which information about past inputs is stored (classically or quantum-mechanically) and how it is transferred from one time step to the next. This work tests both the archetypal QRC of Fujii and Nakajima [8], which uses coherently evolving memory qubits, as well as quantum extreme learning machines (see, e.g., [17, 18, 19, 20]), which possess no quantum memory but process explicitly time-delay-embedded input. Following a common choice [8, 21, 22, 23], each of these is employed, as a default, with a transverse-field Ising Hamiltonian for the unitary reservoir evolution between consecutive inputs. Its coupling values and the evolution time are hyperparameters, the same holds for the encoding of each reservoir input (e.g., amplitude or rotational encoding). Despite these particular choices, we expect that the insights gained with these are also informative for surrogates based on other QRC variants.

Besides establishing a proof-of-concept in an established benchmark, ablation studies in the model components can be carried out, concerning both quantum-specific components (e.g., choice of encoding, Hamiltonian and observables) as well as reservoir-generic components (e.g., selection of input features).

3 Practical demonstration

As mentioned above, in principle, the proposed surrogate modeling is a hybrid quantum-classical machine learning approach, with nonlinear feature generation and temporal memory provided by the quantum system, and (ridge) regression of the reservoir readout performed by the classical CPU. However, in the context of the present work, the quantum reservoir is still treated as an idealized few-qubit system undergoing unitary evolution and is thus easily simulated in a statevector simulation using the QuTiP quantum toolbox in Python [24]. (If time permits and the idealized setup produces encouraging results, the QRC-based modeling can be further probed under more difficult, yet realistic conditions including decoherence and noise effects, in particular noise channels or shot noise affecting the reservoir readout.)

The model hyperparameters are optimized using `optuna` [25], while the (Tikhonov-)regularized linear regression, also known as ridge regression [26, 27], is solved using implementations provided by `scikit-learn` [28].

Following reference [29], the short-term forecast quality is quantified via the fit factor Q (roughly corresponding to 1 - NRMSE), comparing the costly CFD-generated time series for lift and pitching moments to the series' obtained by the trained (and hyperparameter-optimized) quantum reservoir computer.

So far the methodology has being probed mainly on sinusoidal gust excitations. For such gusts we find that the QRC-based surrogates indeed are able to predict gust responses in unseen in-between gust configurations with high fidelity (fit factor above 95 percent). (As this is an ongoing project, it is also planned to extend the investigation to discrete, so-called '1-cos' gusts.)

Furthermore, following a simple divide-and-conquer strategy, we find that when attempting to cover a two-dimensional gust parameter space (amplitude and period length) with one-dimensional parameter slices along each of which a parameter-aware QRC is trained to interpolate, the difficulty of the learning problem strongly depends on the slicing direction (i.e., which parameter to keep fixed for bundling the co-trained time series). We discuss this in light of the fixed and finite memory capacity of the reservoir and discuss how this can partly be mitigated by an adaptive sampling strategy accompanying the parameter input channel.

Although, at least at the time of writing, the quantum statevector simulations carried out in this work are mostly agnostic to the quantum hardware platform and do not yet include potential major experimental obstacles (e.g., noise channels, shot noise), we regard this level of idealization at this initial level of exploration as acceptable, as the focus is rather on a proof-of-concept for the use case at hand and on the mentioned ablative dimensions that already arise at this stage. Moreover, several works already suggest that certain forms of (mild) noise and dissipation can even enhance the temporal processing and generalization [8, 30, 31, 32, 33], which intuitively may prevent overfitting or enforce the fading memory property of the reservoir. This allows for some optimism that a practical demonstration under idealized conditions stays informative and constitutes a solid foundation for subsequent research.

4 Application potential

The presented approach of a QRC-based surrogate model has been demonstrated exemplarily in this work for the gust response prediction of a two-dimensional airfoil. Typical CFD mesh sizes of current transport aircrafts are associated with an increased model size by a factor of 50 to approximately 200. If the number of CPUs that is used for the CFD simulations remains the same, the computing times required to generate the training data increase accordingly. With regard to the global coefficients, however, there are no fundamental qualitative differences in the gust responses in comparison between the two-dimensional airfoil and the three-dimensional

transport aircraft, see [3]. Hence, the subsequent process of the QRC could probably remain analogous to the approaches presented here and there is no obvious reason to expect that the resource demands — either the number of qubits or the classical computational ressources (say for performing the ridge regression) — necessarily become prohibitive. However, as is also the case with non-quantum surrogates and in particular conventional RC (Echo State Networks, Next-Generation-RC), the applicability of a machine learning method can hardly conclusively be judged without explicit experimentation, even less the required model expressivity in its precise interdependency with forecast quality. Thus, a load analysis on a commercial aircraft configuration, e.g., in the preliminary design, which is based on QRC-based surrogate models, could therefore benefit from a substantial saving in computational time, although, a reliable, numerical estimate is not possible at the present time.

Remarks: While computation time comparisons are not yet aimed for in this work, some remarks are in order. First, the overall computation time for a complete forecast along the full parameter space depends on the distribution of workload between the CFD and surrogate components (percentual split, if assuming that the CFD-computations are equally costly in all parameter points). This, in turn, couples closely to the forecast quality of the surrogate model, which is expected to decrease when provided with less training data. The trade-off here also relates to the maximum tolerable approximation error, as defined by the user (or regulator). Before diving into these considerations, a working machine learning pipeline that enables tolerable error values in the first place (ignoring computational time) must be established.

Second, all-inclusive time measurements also depend on a multitude of components along the whole machine learning pipeline, most importantly on the quantum simulation method (e.g., full statevector or matrix product state simulation), but potentially also on the ridge regression solver, hyperparameter optimization or even choice of software revisions. For fair comparisons, these eventually would also need to be optimized to be benchmarked against highly optimized CFD-code.

Finally, net computational times in a real hybrid quantum-classical implementation, which is the mid- to longterm goal if one is not rather investigating *quantum-inspired* methods, would additionally depend on the experimental specifics of the chosen quantum hardware (also via their influence on forecast quality). This falls outside the scope of the current work.

Acknowledgement

This project was made possible by the DLR Quantum Computing Initiative and the Federal Ministry for Research, Technology and Space; qci.dlr.de/en/nemoqc/

References

[1] W. Weigold, B. Stickan, I. Travieso-Alvarez, C. Kaiser, and P. Teufel, "Linearized Unsteady CFD for Gust Loads with TAU," in *International Forum on Aeroelasticity and Structural Dynamics*, 2017. IFASD-2017-187.

[2] P. Bekemeyer, *Rapid Computational Aerodynamics for Aircraft Gust Response Analysis*. PhD thesis, University of Liverpool, 2018.

[3] D. Friedewald, *Gust-Induced Amplitude Effects in Transonic Flow*. PhD thesis, Technische Universität Braunschweig, 2025.

[4] C. Kaiser, D. Quero, and J. Nitzsche, "Quantification of Nonlinear Effects in Gust Load Prediction," in *International Forum on Aeroelasticity and Structural Dynamics*, 2019. IFASD-2019-054.

[5] R. Thormann and M. Widhalm, "Linear-Frequency-domain predictions of Dynamic-Response data for viscous transonic flows," *AIAA Journal*, vol. 51, pp. pp. 2540–2557, Nov. 2013.

[6] W. Maass, T. Natschläger, and H. Markram, "Real-Time Computing Without Stable States: A New Framework for Neural Computation Based on Perturbations," *Neural Computation*, vol. 14, pp. 2531–2560, Nov. 2002.

[7] H. Jaeger and H. Haas, "Harnessing Nonlinearity: Predicting Chaotic Systems and Saving Energy in Wireless Communication," *Science*, vol. 304, pp. 78–80, Apr. 2004. Publisher: American Association for the Advancement of Science.

[8] K. Fujii and K. Nakajima, "Harnessing disordered-ensemble quantum dynamics for machine learning," *Phys. Rev. Appl.*, vol. 8, p. 024030, Aug 2017.

[9] T. Gerhold, M. Galle, O. Friedrich, and J. Evans, "Calculation of complex three-dimensional configurations employing the DLR-TAU-code," in *35th Aerospace Sciences Meeting and Exhibit*, Jan. 1997.

[10] D. Schwamborn, T. Gerhold, and R. Heinrich, "The DLR TAU-Code: Recent Applications in Research and Industry," in *European Conference on Computational Fluid Dynamics (ECCOMAS)* (P. Wesseling, E. Onate, J. Periaux, ed.), Sept. 2006.

[11] C. Kaiser, R. Thormann, D. Dimitrov, and J. Nitzsche, "Time-Linearized Analysis of Motion-induced and Gust-induced Airloads with the DLR TAU Code," in *Deutscher Luft- und Raumfahrtkongress*, 2015.

[12] P. H. Cook, M. A. McDonald, and M. C. P. Firmin, "Aerofoil RAE 2822: pressure distributions, and boundary layer and wake measurements," Tech. Rep. AGARD-AR-138, AGARD, North Atlantic Treaty Organization, 1979.

[13] R. Xiao, L.-W. Kong, Z.-K. Sun, and Y.-C. Lai, "Predicting amplitude death with machine learning," *Physical Review E*, vol. 104, p. 014205, July 2021. Publisher: American Physical Society.

[14] M. Roy, S. Mandal, C. Hens, A. Prasad, N. V. Kuznetsov, and M. Dev Shrimali, "Model-free prediction of multistability using echo state network," *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 32, p. 101104, 10 2022.

[15] D. E. Ozan and L. Magri, "Data-driven computation of adjoint sensitivities without adjoint solvers: An application to thermoacoustics," Nov. 2024. arXiv:2404.11738 [physics].

[16] D. Köglmayr and C. Räth, "Extrapolating tipping points and simulating non-stationary dynamics of complex systems using efficient machine learning," *Scientific Reports*, vol. 14, no. 1, p. 507, 2024.

[17] L. Innocenti, S. Lorenzo, I. Palmisano, A. Ferraro, M. Paternostro, and G. M. Palma, "Potential and limitations of quantum extreme learning machines," *Communications Physics*, vol. 6, p. 118, May 2023. Publisher: Nature Publishing Group.

[18] W. Xiong, G. Facelli, M. Sahebi, O. Agnel, T. Chotibut, S. Thanasilp, and Z. Holmes, "On fundamental aspects of quantum extreme learning machines," *Quantum Machine Intelligence*, vol. 7, p. 20, Feb. 2025.

[19] A. D. Lorenzis, M. P. Casado, N. L. Gullo, T. Lux, F. Plastina, and A. Riera, "Entanglement and Classical Simulability in Quantum Extreme Learning Machines," Oct. 2025.

[20] T. Dao *et al.*, "Breaking concentration barriers for quantum extreme learning on digital quantum processors," 3 2026.

[21] A. Kutvonen, K. Fujii, and T. Sagawa, "Optimizing a quantum reservoir computer for time series prediction," *Scientific Reports*, vol. 10, p. 14687, Sept. 2020. Publisher: Nature Publishing Group.

[22] R. Martínez-Peña, G. L. Giorgi, J. Nokkala, M. C. Soriano, and R. Zambrini, "Dynamical Phase Transitions in Quantum Reservoir Computing," *Physical Review Letters*, vol. 127, p. 100502, Aug. 2021. Publisher: American Physical Society.

[23] J. Steinegger and C. Räth, "Predicting three-dimensional chaotic systems with four qubit quantum systems," *Scientific Reports*, vol. 15, p. 6201, Feb. 2025. Publisher: Nature Publishing Group.

[24] N. Lambert, E. Giguère, P. Menczel, B. Li, P. Hopf, G. Suárez, M. Gali, J. Lishman, R. Gadhvi, R. Agarwal, A. Galicia, N. Shammah, P. Nation, J. Johansson, S. Ahmed, S. Cross, A. Pitchford, and F. Nori, "Qutip 5: The quantum toolbox in python," *Physics Reports*, vol. 1153, pp. 1–62, 2026. QuTiP 5: The Quantum Toolbox in Python.

[25] T. Akiba, S. Sano, T. Yanase, T. Ohta, and M. Koyama, "Optuna: A next-generation hyperparameter optimization framework," in *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2019.

[26] A. E. Hoerl and R. W. Kennard, "Ridge regression: Biased estimation for nonorthogonal problems," *Technometrics*, vol. 12, no. 1, pp. 55–67, 1970.

[27] A. E. Hoerl and R. W. Kennard, "Ridge regression: Applications to nonorthogonal problems," *Technometrics*, vol. 12, no. 1, pp. 69–82, 1970.

[28] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

[29] R. Zahn and C. Breitsamter, "Airfoil buffet aerodynamics at plunge and pitch excitation based on long short-term memory neural network prediction," *CEAS Aeronautical Journal*, vol. 13, no. 1, pp. 45–55, 2022.

[30] F. Monzani, E. Ricci, L. Nigro, and E. Prati, "Enforcing Fading Memory of Noisy Quantum Echo State Networks," in *2024 IEEE International Conference on Quantum Computing and Engineering (QCE)*, vol. 02, pp. 476–477, Sept. 2024.

[31] A. Sannia, R. Martínez-Peña, M. C. Soriano, G. L. Giorgi, and R. Zambrini, "Dissipation as a resource for Quantum Reservoir Computing," *Quantum*, vol. 8, p. 1291, Mar. 2024. arXiv:2212.12078 [quant-ph].

[32] N. Götting, S. Wilksen, A. Steinhoff, F. Lohof, and C. Gies, "Connection between memory performance and optical absorption in quantum reservoir computing," Oct. 2025. arXiv:2501.15580 [quant-ph].

[33] L. Domingo, G. Carlo, and F. Borondo, "Taking advantage of noise in quantum reservoir computing," *Scientific Reports*, vol. 13, p. 8790, May 2023. Publisher: Nature Publishing Group.