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Annotated Bibliography

Strozier, J.A., et al. "Wake Vacuum Measurement and Analysis for the Wake Shield Facility Free Flying Platform." *Vacuum*, vol. 64, no. 2, 2002, pp. 119–144. Elsevier, doi:10.1016/S0042-207X(01)00383-9.

Summary
Strozier et al. report the first in orbit pressure, and temperature measurements taken on NASA's 12-ft Wake Shield Facility (WSF) during its 1995–96 free-flight missions (STS-69 and STS-80). The WSF disk was designed to exploit the ultra-high vacuum expected in the aerodynamic "wake" behind a spacecraft for Molecular Beam Epitaxy (MBE) film growth. Using four cold cathode gauges and distributed thermostats, the team were able to log 1,000+ pressure points per 94-min orbit on both the ram and wake sides. Monte-Carlo models had predicted a six-order ($10^{-8} \rightarrow 10^{-14}$ Torr) pressure drop in the wake.
However, in practice they were only able to observe a two order reduction, accompanied by large, orbit-scale (~100×) diurnal swings that peaked at orbital sunset. The authors attribute the shortfall to solar-driven thermal desorption of water from stainless-steel surfaces and to internal outgassing of the gauges themselves. These effects were amplified when Ga from an over heated source cell coated the chassis on the second flight. Ram side data, by contrast, tracked the Jacchia (1970) thermospheric density model, validating that model experimentally for the first time. A thermal desorption model combining geometry factors and temperature dependent outgassing rates reproduced both the DC wake pressure and the phase-shifted oscillation, and suggested that, with thorough pre-flight degassing ($<3 \times 10^{7}$ molecules cm^{-2} s^{-1}), pressures near 10^{-14} Torr remain achievable.
Credibility
The article appears in *Vacuum* (Elsevier, 2002), a peer reviewed journal specialising in surface science and low-pressure technology. The lead author team comes from the University of Houston's Space Vacuum Epitaxy Center, the group that conceived and flew the WSF, giving them first-hand access to flight hardware and telemetry. The study cites both foundational wake vacuum theory (Melfi, Hueser, Naumann) and contemporary Monte-Carlo work, demonstrating engagement with prior literature.The 22-page analysis, including derived desorption energies (~0.8 eV) and geometric scattering factors, shows rigorous quantitative treatment, although some constants were fitted to match data and would benefit from independent verification. Overall, the combination of peer review, direct experimental access, and transparent error analysis render the source highly credible for technical design insights, while reminding readers to treat absolute pressure figures with caution
Connection
SpaceForgeOS aims to replicate WSF-type wake growth conditions for orbital semiconductor deposition. This paper offers actionable guidance on three fronts:

1. **Pressure Floor & Bake-Out** – The finding that incomplete degassing limited wake pressure to ~10^{-9} Torr suggests we must schedule an extended on-orbit bake to reach the 10^{-13} – 10^{-14} Torr goal. Incorporating a pre-growth "outgassing timer" into the

scheduler, and logging true outgassing rate rather than net pressure will tighten simulation fidelity.

2. **Thermal-Desorption Dynamics** – The observed 1/4-orbit phase lag between ram and wake pressures, driven by solar heating, will be embedded in the ST-GNN training data so the AI scheduler anticipates diurnal spikes that could jeopardise layer purity. Temperature nodes for chassis, shield, and source cells already in our graph can directly ingest the 50–70 degrees celsius cyclic range reported here.

Beringer, Dennis B., et al. "Space Ultra-Vacuum Facility." NASA, Marshall Space Flight Center, Patent No. US5092545A, filed May 8, 1986.

Summary

This NASA patent (Case No. MFS-28139-1) lays out the conceptual design, deployment sequence, and operating method for a “Space Ultra-Vacuum Facility” created around a truncated, hollow hemispherical wake-shield. The shield’s convex face carries the material processing site at its apex and is oriented toward the orbital wake; all power, control, and attitude-keeping hardware rides on the concave face, which points into the ram flow. By removing walls from the line of sight of the growth surface and pushing out-gassing subsystems upwind, the geometry blocks both direct molecular out flux and back-scattered ram molecules, enabling vacuum levels that ground chambers struggle to reach (targeting =< 10^-12 Torr).

The patent describes a carousel that indexes multiple substrates under extendable fixtures: (1) a micro-gravity molecular-beam-epitaxy (MBE) gun; (2) an optical diagnostics head for in-situ monitoring. The deployment process includes: (i) grapple and release from the Shuttle bay, (ii) fly convex-face-forward to let ambient atomic oxygen scrub hydrocarbons, (iii) sun-pointing “bake-out” to drive off residual volatiles, and (iv) flip to the operational attitude (concave face forward, convex face in the wake) for growth runs. Next, the free flying platform is retrieved by the Shuttle arm. The inventors argue that the arrangement slashes contamination risk, shrinks on orbit cleaning costs by exploiting natural atomic oxygen and solar heating, and opens paths not only for MBE but also mirror coating, materials ultra-purification, and fundamental surface studies.

Credibility

This disclosure emanates directly from NASA’s Marshall Space Flight Center. The organization that ultimately built and flew the Wake Shield Facility (WSF). The document furnishes detailed schematics, materials choices (low-out-gassing stainless steel), and step by step flight operations, reflecting engineering grade rigor rather than speculative theory. Performance claims rest on analysis and sub-scale tests available at the time (1986 filing); key vacuum figures were only fully assessed in-flight years later. In sum, the source is authoritative for system architecture and operational logic, with the usual caveat that quantitative promises pre-date full-scale verification.

Connection

We can adopt the three-stage conditioning loop: atomic-oxygen scrub, solar bake-out, then flip the spacecraft using attitude control. Embedding those maneuvers into our attitude-control sequences should let us hit the out gassing thresholds demanded by our simulation (=< 3 × 10^7 molecules cm^-2 s^-1) without adding massive heater mass.

Rubanova, Yulia, et al. "Constraint-Based Graph Network Simulator." *arXiv*, 28 Jan. 2022, arXiv:2112.09161.

Summary

This paper introduces C-GNS, a learned physics engine that implicitly represents dynamics with a single scalar constraint function implemented as a graph neural network. At every step the simulator searches, via gradient descent, for the next system state that minimizes this learned constraint, rather than predicting the state outright Constraint-based graph. Across ropes, rigid bodies, and fluids, C-GNS matches or beats strong forward prediction baselines while offering two unique levers: (i) extra solver iterations at test time trade compute for accuracy, and (ii) hand designed constraints can be injected on the fly to generalise to novel tasks or larger systems.

Credibility

The work comes from DeepMind's graph networks team; also behind Interaction Networks and MeshGraphNets, and continues their run of highly cited simulation papers. Although still a pre-print, the manuscript provides extensive ablations, open sourced code, and detailed comparisons against ICML/ICLR benchmarks, reflecting the group's typical rigour.

Connection

SpaceForge's orbital deposition model must strictly adhere to the hard power budget, and chamber pressure limits. Whilst doing its best to reach the goal of running the platform 24x7. C-GNS's implicit-constraint approach lets us encode those limits directly as differentiable terms (e.g., wattage ceilings, Torr targets) and solve for states that satisfy them, while retaining the scalability of graph simulators. The "extra-iterations-for-accuracy" knob is especially attractive for ground-based planning where latency is looser, yet the same weights can run in real-time onboard with fewer iterations.

Tassel, Pierre, et al. "Semiconductor Fab Scheduling with Self-Supervised and Reinforcement Learning." *arXiv*, 14 Feb. 2023, arXiv:2302.07162.

Summary

Tassel and collaborators tackle full scale wafer fab dispatching: thousands of tools, stochastic events, and mixed product flows using a two stage learning pipeline. A self-supervised pre-text task first learns tool-family embeddings; a single reinforcement-learning agent with global attention then sequences lots to machines, optimising tardiness and cycle-time. On both low-mix/high-volume and high-mix/low-volume simulation test-beds, the method trims overall cost by up to 17 % and doubles on-time completion for regular lots relative to industry heuristics

Credibility

The authors span the University of Klagenfurt, Graz University of Technology, and Infineon Technologies, grounding the study in real industrial experience Semiconductor Fab Sched…. They release code (RL4SemiconductorFabSched) and build on open-source fab simulators, enhancing reproducibility. The paper situates its gains against a comprehensive survey of dispatching heuristics and prior RL attempts, underscoring a meaningful leap in scale and realism.

Connection

SpaceForge's in-orbit deposition scheduler faces a parallel challenge to terrestrial semiconductor fabs: coordinating multiple energy intensive subsystems such as localized heaters, plasma jets, thermal shutters, and substrate rotation arms—while operating within strict constraints on total power, thermal load, and time. Like fab tools, these elements form a heterogeneous resource pool with different capabilities, costs, and warm up or cool down profiles. Tassel et al.'s architecture provides a two-phase blueprint to manage this complexity in a way that's learnable, generalizable, and ultimately deployable on edge hardware.

The self-supervised pre-training phase in their system learns tool family embeddings, which could translate in SpaceForge to latent vector representations of heater banks, pump modules, or deposition zones. In this use case, each embedding captures traits such as power efficiency, temperature stability, or outgassing behavior. These embeddings give the scheduler semantic awareness of how different devices behave under different loads or process stages, enabling it to learn nuanced trade offs (e.g., when to reassign a task to a slower but cooler device to stay within a thermal envelope).

The RL agent, trained atop these embeddings, then acts as the dispatcher: sequencing deposition, outgassing, and cooldown operations to maximize overall throughput (e.g., wafer completion or film layer accuracy) while obeying the system's real-time power budget. This is essential in SpaceForge's orbital context, where available wattage is capped by solar input and battery state, and any overdraw could trigger system throttling or failures. Moreover, the agent's use of global attention mechanisms allows it to track and prioritize across dozens, or potentially hundreds of concurrent substrates or process stages, much like in the fab simulations.

Finally, their use of derivative-free optimization and attention over multi-task queues directly supports SpaceForge's need for online learning or adaptive scheduling in uncertain conditions (e.g., material variation, solar shadowing, or thermal lag). Taken together, Tassel et al.'s method offers a roadmap for how to move from rigid, rule based scheduling toward a data-driven, adaptive control layer that is both power-aware and throughput-optimized. Which is precisely the kind of system required for a next gen autonomous orbital fabrication.

Battaglia, Peter W., et al. “Relational Inductive Biases, Deep Learning, and Graph Networks.” *arXiv*, 12 Oct. 2018, arXiv:1806.01261.

Summary

Battaglia et al. articulate a unified framework for representing structured entities and their relations using what they call *Graph Networks (GNs)*. Which are a modular generalization of various prior graph neural network architectures. The core thesis is that incorporating relational inductive biases; biases that reflect how entities (nodes) interact through relations (edges) is essential for modeling complex systems such as physical simulations, social interactions, and molecular structures. Their GN block computes node, edge, and global updates using learnable functions and supports customizable logic per edge type or relation. The paper situates GNs as a middle ground between traditional physics engines (with hand written rules) and black box deep learning models, enabling learned models that still respect system structure. Extensive examples are presented from physical reasoning tasks, relational reasoning, and combinatorial generalization.

Credibility

This paper originates from DeepMind’s research team, including pioneers in differentiable physics simulation and deep learning for reasoning. It has become a canonical reference in the GNN literature, with over 6,000 citations and a significant influence on subsequent works such as MeshGraphNets, C-GNS, and GNS. It is widely used in both academic and applied settings due to its strong theoretical grounding and reproducible implementations.

Connection

SpaceForgeOS models a highly structured physical system where energy, heat, pressure, and materials interact via distinct pathways. Exactly the kind of multirelational entity interaction described in this paper. The GN formalism lets us define type-specific edge update functions (e.g., energy vs. pressure) while maintaining a common interface for temporal prediction. This supports the construction of interpretable, physics informed spatio-temporal schedulers that scale with system complexity. Moreover, the GN architecture can serve as a foundation for the constraint-respecting, edge-type modular ST-GNN needed for realistic orbital process control in SpaceForge.

Cuéllar Carrillo, Sara, et al. "Explainable Anomaly Detection in Spacecraft Telemetry." *Engineering Applications of Artificial Intelligence*, vol. 133, 2024, article 108083.

Summary

This paper proposes a hybrid anomaly detection system that combines recurrent neural networks (RNNs) with SHAP (SHapley Additive explanations) to diagnose irregularities in spacecraft telemetry. The authors focus on time-series sensor data and show how SHAP can identify which input signals most influence anomaly classifications. Their model is trained and validated on satellite telemetry datasets, producing not only alerts but also human readable explanations for each flagged event.

Credibility

Published in a high impact journal and backed by a consortium of European aerospace researchers, the study reflects cutting-edge applications of XAI in mission-critical settings. The authors demonstrate both strong experimental design and domain familiarity, using real world datasets from ESA and adhering to stringent validation protocols.

Connection

In our system, real-time sensor feeds from deposition chambers (e.g., pressure, flow, power draw) may spike during orbital operations. Integrating a similar XAI-based anomaly detection pipeline would let us trace anomalies not only to values but to their likely causes. Thus enhancing the overall safety, preventing component damage, and supporting autonomous corrections. This approach strengthens our reliability goals in low-maintenance environments like LEO foundries.