

## Industrial design process as scientific discovery

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In industrial design, we do not study a phenomenon of nature that exists separately from humans, but rather something that we are aiming to create in response to a design problem. Building a naval ship that fits in the monetary budget, integrates modern technologies, maintains survivability, and can be repaired is an example of a design problem. “Design” as a noun might refer to the final adopted solution, whereas “design” as a verb is a process that somehow, sometimes results in that solution. Design, thus, is a process of generating knowledge for decision-making through time. The design problem is wicked: it starts not as a mathematical question, but as a collection of customers’ briefs and stakeholders’ interests and lacks an obvious stopping point for our solution attempts. In order for the mathematical tools to be useful in finding design solutions, they first need to help us understand the design problem. The connection of the problem space to the solution space is often nontrivial and waiting to be discovered.

In order to turn the wicked, ill-posed design problem into a mathematical form, we need to make choices about the space of allowed solutions, and the values of design objectives reached by each solution. While individual design objectives might be known, the central issue of modern design is system integration: how do we reach a system that performs best overall, even if it compromises on individual functions? The combinatorial space of system configurations is exponential in the number of elements and thus impossible to review manually.

One way to proceed is automating the combinatorial search via an optimization algorithm that minimizes the cost function. However, optimization is fundamentally a reductive technique: it tells us about the “best” solution at the expense of ignoring all others. Optimization conflates the question with one option of an answer, and thus does not provide us with an improved understanding of the problem. Some optimization problems have “rough” landscapes, or are over-constrained, so that finding the single true global minimum of a cost function, as opposed to the many local minima, is computationally challenging. Other optimization problems suffer from the opposite issue: they are too “flat” or under-constrained, so that the global minimum is trivially easy to find but is not informative, as it is not meaningfully different from the surrounding solutions. Yet at both extremes the optimization paradigm suffers from the same two shortcomings: it doesn’t build intuition for how typical design solutions change with the shifting problem statement, and lacks language to acknowledge the solution entropy. We show that keeping track of these two factors reveals a wealth of new behaviors in design problems.

In our paradigm of Systems Physics, we approach design problems from the alternative mathematical viewpoint of statistical mechanics. Statistical mechanics naturally captures the combinatorial space of solutions weighted by the cost function but replaces the strict exclusive optimization with a probabilistic suppression of suboptimal solutions. As a result, we can study the whole mapping from the space of design objectives onto the space of preferred solutions. Through this mapping, we can understand whether changing design objectives cause solutions to vary smoothly or abruptly and whether different design objectives are compatible or contradictory. The mathematics of coarse graining allow us to study the effective cost landscape of one subsystem by marginalizing the other ones. These effective landscapes work just like potential energy in classical mechanics, which we routinely use to reason about effective forces and stability of solutions.

Systems Physics was developed as a broad paradigm for different problem spaces, but needed to be shown in a specific application area, in our case a ship design problem from naval engineering. In placing the shipboard equipment and its interconnections, the designers need to carefully balance the needs to minimize cost yet keep flexibility in connections. We explored this fundamental trade-off across four case studies and discovered multiple design space phenomena like those known in condensed matter physics.

First, we show that the balance of cost and flexibility gives rise to an abrupt and large-scale phase transition between the architecture classes of short and cheap versus long and expensive routings. The phase transition is driven by the emergent attraction and repulsion of functional units. Second, we consider the robustness of architecture classes with respect to external connections. Instead of focusing on which solution is more optimal, we describe the robustness in the language of weak-strong and brittle-robust from materials science. Third, we study the problem of shipboard system arrangements across the axes of both spatial and topological detail. From this spatial-topological interplay we distill several emergent phenomena, including symmetry breaking, emergent correlation, and emergent localization of functional units. Fourth, we consider the effect of the cost-flexibility trade-off on the appearance of clustering vulnerabilities in the system. We find clusters to routinely appear in both cost- and flexibility-dominated regimes, and to only disappear in the intermediate regime; however, the disappearance of clusters requires high design uncertainty, thus establishing a no free lunch result for design problems.

Across the four case studies, we were primarily concerned with the trade-off between an explicitly known objective (solution cost) and an emergent one (solution entropy). In systems with multiple explicit objectives more complex trade-offs might be possible. Advancing one objective might have different effects on another objective: it might advance proportionally, or not change at all, or even regress. In order to account for all these options, one might measure the pairwise “angle” between the objectives and find whether it is acute, nearly right, or dull. Mapping out the objective angles would support the arguments of whether the interests of different stakeholders in the problem can be in principle balanced.

The mapping from candidate solutions to the design objectives they achieve can be thought of as “forward” design; it is contrasted with the “inverse” design searching for a solution that reaches a target objectives. We desire certain material properties and search for synthesis pathways; or aim for target focal distance and aberration and fiddle with composite lens systems. In trying to solve these problems not as one-offs but as representatives of a class, we do not just design in the forward or inverse direction, but try to discover repeatable, robust patterns in solutions, which we can term design rules. The discovery of design rules is always positioned between the detailed solution and the whole design space, requiring a study of intermediate scales of detail.

Across this arc of studies, we establish that design is a new frontier for study of scientific discovery. Design discoveries do not always amount to either “fundamental” or “reduced” dynamics, because the phenomena are often not dynamical in nature. Systems Physics offers one perspective on how to study design quantitatively, but not reductively, grounded in analogies with condensed matter physics. We expect that many other analogies can be fruitfully drawn, from evolutionary principles of solution course to group dynamics of designers with different expertise. Beyond naval engineering, many other problems have combinatorial search spaces with nontrivial objective trade-offs. Lastly, the discovered design phenomena need to be validated empirically, requiring us to develop a notion of “experiment” in design.

## References

- [1] A. A. Klishin, D. J. Singer, and G. van Anders, Avoidance, Adjacency, and Association in Distributed Systems Design, *Journal of Physics: Complexity*, 2.2 (2021): 025015, <https://iopscience.iop.org/article/10.1088/2632-072X/abe27f/meta>
- [2] A. A. Klishin, A. Kirkley, D. J. Singer, and G. van Anders. Robust Design from Systems Physics. *Scientific Reports*, 10.1 (2020): 14334, <https://link.springer.com/content/pdf/10.1038/s41598-020-70980-5.pdf>
- [3] A. A. Klishin, C. P. F. Shields, D. J. Singer, and G. van Anders. Statistical Physics of Design. *New Journal of Physics*, 20.10 (2018): 103038, <https://iopscience.iop.org/article/10.1088/1367-2630/aae72a/meta>