logan@unr.edu // Logan Yliniemi, Asst. Professor, University of Nevada, Reno // (775)682-7479

L. Yliniemi (UNR) Research Summary

As an assistant professor at the University of Nevada, Reno, my work focuses on the optimization of large, messy, difficult to model systems. I have done work in areas such as air traffic management, rover exploration, truck fleet management, hybrid power generation, and microgrid coordination. A common tenet among these types of problems is that it is extremely difficult to enumerate exactly what a good solution looks like in a single quantity.

For example, in air traffic management, it is not enough to say that all flights should be on time: this leads to the trivial solution of reducing the number of flights to zero. Instead, we must enumerate our desires to (i) maximize on-time arrivals, (ii) minimize congestion, and (iii) meet passenger load demands. These three conflicting objectives create a **multi-objective optimization (MOO)** problem, which is a well-studied field in its own right. However, because the solution to this problem is inherently distributed, with traffic controllers all over the country affecting the load on other airports far removed from their own, this is also a **decentralized multiagent system (MAS)** problem, also a field in its own right. This combination of MOO and MAS creates a **multi-objective decentralized multiagent system (MOMAS)** problem, which is my area of expertise, and an area that has only recently attracted research interest.

Within the field of multiagent systems, I use a variety of modern credit assignment techniques, which each serve to give each agent (an air traffic controller in the example above) a clear, concise picture of how well its performance helped the system as a whole. Such techniques include Difference Evaluations, Leniency, and Hall-of-Fame techniques. I have a publication record which supporting my ability to use these techniques effectively.

To deal with multi-objective problems, I have personally developed an up-and-coming technique known as the Pareto Concavity Elimination Transformation (PaCcET). PaCcET functions by conditioning MOO problems to be easier to solve, instead of making a more complicated solution strategy. Figure 1 shows how PaCcET transforms the set of optimal solutions (the "nondominated set" or NDS) to be a straight line, of equal value to a fast-executing linear combination optimization.

PaCcET has shown to execute over 10 times faster than competing state of the art methods like NSGA-II, and in preliminary work, we have also obtained results on a microgrid control domain where **PaCcET obtains better performance using only 1/3 of the samples**, where each sample can be complex to obtain. These two properties uniquely suit it for solving complex optimization problems like those found in MOMAS.

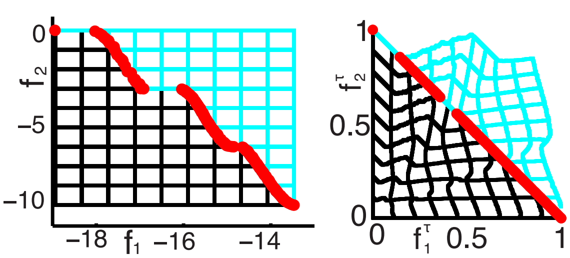

Figure 1: PaCcET allows difficult nonlinear problems to be solved with linear techniques, increasing solution quality while slashing computation time.

Beyond the technical skills required by the individual fields, a common tenet among these types of complex optimization problems is that obtaining a meaningful model of the correct precision for use by techniques developed within those fields of study can be difficult or expensive. As an example, the HyPER facility in West Virginia uses many empirical transfer functions (ETF) to control their facility, where each ETF is *expensive to obtain*, *limited usefulness* — only in a very small operating regime due to strong nonlinearities — and *invalidated upon changes to the system.*

In contrast, instead of relying on these high-fidelity models and building techniques around them, I instead focus on building model-free stochastic optimization techniques. By using a simulation as a model, we can try thousands or millions of solutions for the same costs as just a few experimental runs. These simulations have shown in the past to be of high enough fidelity to result in viable controllers when applied to the physical system.