# Dynamic Energy Management

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## 1 Background

There are many optimizations that must occur to effectively manage the electric power grid, including Security-Constrained Unit Commitment (SCUC), Security-Constrained Optimal Power Flow (SCOPF), Economic Dispatch, Loss Minimization, Reactive Power Compensation, et. al. As the size and complexity of these optimization problems grow, the need to solve these problems in a timely manner with a larger number of features and data sets becomes increasing challenging.

Alternating Direction Method of Multipliers (ADMM) is an algorithm that utilizes a decomposition coordination method whereby a large problem is decomposed into small local sub-problems that are coordinated in a manner that solves the larger global problem. ADMM blends the benefits of dual decomposition methods and augmented Lagrangian methods (ALM) to solve large scale optimization problems using a scalable approach, based in part on discovering optimal dual variables (marginal prices). This research work is focused on operationalizing the ADMM algorithm to support production electric power management.

## 2 Research Outline

The proposed research is split across two years, with the first year constraining the scope to a simplified optimal power flow problem (convex only), solved via a centralzied method, and extending the problem to the distributed setting in year two. The following section describes more specific activities associated across each year.

### 2.1 Year One

In the first year we will concentrate on developing a foundational open source Python package for dynamic energy management, following the abstract ideas laid out in [KCLB14], and focussing entirely on the convex case. We hope that the package will support multiple types

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of dynamic energy optimization problems, including day-ahead 15 minute planning, but also including hydro resource management, minute-by-minute planning, and even optimal management of a hybrid vehicle. This package will be based on CVXPY [DB16], a open source convex optimization package in Python.

1. *Defining the classes and methods.* The first task is to identify the mathematical structure of the dynamic energy problems and develop Python code to support the abstractions.

2. *Implementing classes.* We will carefully define the critical classes, including generators, storage devices, transmission lines, basic loads, smart loads including deferrable loads, curtailable loads, HVAC loads, and connections to other sources with time varying prices and availability. We will include several classes of green energy sources, including wind and solar, possibly coupled with local storage and/or generators.

3. *Adding additional methods.* We will define the critical methods used to connect device objects, optimize energy consumption and generation over a time interval, retrieve time varying optimal prices at a bus or other energy exchange point, and so on.

4. *Benchmarking.* We will work with MISO to benchmark and analyze the scalability of the centralized algorithm.

5. *User interface.* We will work with MISO to develop simple UIs, code to translate standard descriptions into our package code, possibly via XML.

**Year One Research Scope.**

1. *Convex problems only.* Year one work will focus entirely on convex problems, since in this case the optimization is clear, and we can rely on CVXPY as the base optimization layer. In particular, year one will focus on (real) power flow, and not the more traditional voltage and current phasors, or real and reactive power flows. This model can be made to include many realistic power systems, and will include, for example, variable generator cost, generator minimum and maximum powers, various types of smart loads, DC and AC transmission line losses, storage energy and power limits, generator ramp rate limits.

   MISO will be applying and evaluating ADMM / CVXPY against a simplified (linearized) Security Constrained Unit Commitment (SCUC) problem. Although we do not expect any direct support for this parallel SCUC problem research, we anticipate some occasional advisory input and guidance to help inform further evaluation of ADMM within a power optimization context.

2. *Centralized solution method.* Year one work will focus on a centralized CVXPY solver (which could be multi-core).

## 2.2   Year Two

Year two will extend the foundational work created in year one to potentially include exploration of the following areas and to help further operationalize the dynamic energy management package.

- *Distributed solution via ADMM.* We will develop methods to automatically split up a large problem and solve it using ADMM.

- *Convex relaxation.* We will explore methods for handling non-convex devices and objectives, including for example on/off loads and generators, AC power flow constraints on loop networks, and other non-convexities.

- *Closed loop control.* We will explore using receding horizon control (RHC) [MWB11, MB] or model predictive control (MPC) [WB10] to adapt schedules in response to external disturbances adapting the solution across an evolving time horizon by incorporating new information as it becomes available.

- *Security constraints.* We will explore the incorporation of security constraints directly in the optimization, by adding a set of contingencies for devices and carrying out planning for operation under nominal and contingent operations.

- *Hierarchical extensions.* We will explore the extension of the model to support the natural hierarchy of the power grid by possibly scheduling messages on different time scales between systems of similar hierarchy.

## 2.3   Future Extensions

The following section outlines additional areas of investigation for operationalizing the ADMM algorithm. These items are considered beyond the scope of this initial two-year effort.

1. *Incentive compatible protocols.* Modifying (if needed) the core ADMM algorithm to be incentive compatible, so the system is robust to non-cooperative or antagonistic devices. This can include bad behavior detection and counter measures to ensure proper system behavior.

# 3   Approach

1. We will develop a framework for running such a system in model predictive control (MPC) mode, using predictions of future values (loads, prices, etc.) over a horizon.

2. We will publish the code under GitHub, with full documentation. We will also prepare a paper to be published on the project. All code will be released under a GNU 3.0 license.

3. We will work with MISO Energy technical contacts to keep them in the loop, ensure that the code we write can be run in their environment, and get general feedback on the organization with short updates occurring on a monthly basis.

4. *Travel.* Stephen Boyd and the assigned graduate student will travel to MISO once each year and the assigned MISO technical resources travel to Stanford a minimum of twice each year.

# References

[DB16]   Steven Diamond and Stephen Boyd. CVXPY: A python-embedded modeling language for convex optimization. *Journal of Machine Learning Research*, 17(83):1–5, 2016.

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[MB]     J. Mattingley and S. Boyd. Automatic code generation for real-time convex optimization. *Convex optimization in signal processing and communications*, pages 1–41.

[MWB11]  J. Mattingley, Y. Wang, and S. Boyd. Receding horizon control: Automatic generation of high-speed solvers. *Control Systems, IEEE*, 31(3):52–65, 2011.

[WB10]   Y. Wang and S. Boyd. Fast model predictive control using online optimization. *IEEE Transactions on Control Systems Technology*, 18(2):267–278, 2010.