Data Reconciliation for Power Plants

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About the Client

Bharat Heavy Electricals Limited (BHEL) is a Public Sector Undertaking in India that deals with engineering, procurement, construction and commissioning of power plants and auxiliary equipments all over the world. Its R & D division at Hyderabad in India not only designs turbines, heat-exchangers, boilers, process ancillary equipment but also provides services towards complete plant integration. The BHEL R & D team has long implemented optimized design principles for overall plant configuration.

Motivation

Process performance estimation and optimization are of prime importance in power-plants and are often limited by inconsistent measurements coming from the plethora of sensors spread across the plant. Design principles require all measurements to be consistent and satisfy the model constraints. Real time measurements may have either random or gross errors (such as sensor biases) that impact the accuracy of the data. Data Reconciliation (DR) and Gross Error Detection (GED) are twin statistical techniques that have been developed and refined over the last fifty years to systematically improve the accuracy of plant measurements. This in turn would support estimating the efficiency of different equipments within a power-plant including boiler, turbine and electrostatic precipitator. The efficiency estimation is completely dependent on the accuracy of measurements.

Problem

The R & D team at BHEL was tasked with building a framework to configure a power-plant and provide consistent estimates from raw streaming sensor readings at all sensor stations, spread across any given plant. The challenge was to integrate the well established Refprop [1] thermodynamics module with the strongly tested open-source non-linear optimization code IPOPT [2]. These were together used for mathematically expressing the balance equations of over 50 equipments in the plant as constraint equations involving over 200 variables. The power-plant consisted of two separate steam and flue-gas circuits that exchanged energy in the boiler section. The thermal energy of compressed steam was transferred to the turbines to drive the shaft and ultimately deliver electricity to the grid. The steam cycle underwent phase changes in the heat exchangers and in remained as wet-steam streams in some equipments. Each of these equipments and streams required formulation of their unique model equations and needed robust integration to formulate the data reconciliation problem.

Solution

The object-oriented code architecture was implemented in Python at **Gyan Data** using custom bindings to the Fortran function library of the thermodynamic module Refprop and the C++ based optimizer IPOPT. All equipments available within the power-plant were modeled as new class abstractions possessing attributes and constraint methods describing their balance equations.

The entire power-plant information was configured through an Excel interface from which the Python code could read the measurements and plant configuration.

Based on this interface, the entire constraint equations were assembled using the class definitions of the equipments and streams. For the measured variables a scaled least-squares sum objective cost was formed (scaled with sensor's variance). The entire problem then was passed to the non-linear optimizer IPOPT to evaluate consistent estimates of the measurements and also evaluate unmeasured variables that satisfy all the constraint equations.

Additionally, the reconciled estimates were further processed to evaluate gross-errors (biases) in order to detect faulty sensors. If present, such sensors' measurements were dropped and fresh data reconciliation was performed to ensure that they do not adversely affect the other measurements' estimates. Data reconciliation banks on the redundancy of measurements in a plant and hence also utilized all measurements in the power-plant, even providing new insights for sensor placements.

References

[1] EW Lemmon, ML Huber, and MO McLinder. Nist reference database 23: reference fluid thermodynamic and transport properties-refprop, version 9.1. *National Institute of Standards and Technology, Standard Reference Data Program*, 2013.

[2] Andreas Wächter and Lorenz T Biegler. On the implementation of an interior-point filter line-search algorithm for large-scale nonlinear programming. *Mathematical programming*, 106(1):25–57, 2006.