An Optimal Reference Governor for Hybrid Fuel-Cell/Gas-Turbine as a Distributed Generation Source

Wenli Yang* and Kwang Y. Lee**

* Pennsylvania State University
** Baylor University

February 12, 2010
Outline

• Introduction
• The Hybrid Fuel-Cell Power Plant
• An Optimal Reference Governor
• Optimization Results
• Conclusion
Introduction

• Distributed Generation
  – Use smaller power generation units close to load centers other than centralized power plant
  – Advantages:
    • Reduced power loss
    • Improved power quality
    • Improved reliability
  – DG in Smart Grid
Introduction (Cont.)

• Fuel Cell Power Plants
  – Alternative power source in DG
  – Convert energy w/o combustion
  – Advantages
    • High conversion efficiency
    • Very low emission
    • Fuel flexibility
    • Flexible siting and scalability
Introduction (Cont.)

• The Hybrid Fuel-Cell Power Plant
  – Integration of fuel cells and gas turbine
  – Direct FuelCell/Turbine® (DFC/T)
    • 250 kW Direct FuelCell® (MCFC) + 60 kW Gas Turbine
    • Fuel reformed internally w/o additional reformation devices
    • Expected high fuel efficiency up to 75%
  – Optimal operation problem
    • Cannot reach high efficiency w/o proper operation
    • High complexity of the hybrid power plant
    • Need advanced optimization method
The Hybrid Fuel-Cell Power Plant

- Process Description
  - Gas flow
  - Power flow
The Hybrid Fuel-Cell Power Plant

• Chemical Reactions
  – Fuel reformation
    • In the anode and the pre-converter
      \[ \text{reforming} \quad 3H_4 + H_2O \rightarrow CO + H_2 \]
      \[ \text{water-gass shift} \quad CO + H_2O \rightarrow CO_2 + H_2 \]
  – Electrochemical reactions
    • Anode
      \[ H_2 + CO_3^- \rightarrow CO_2 + H_2O + 2e^- \]
    • Cathode
      \[ CO_2 + \frac{1}{2}O_2 + 2e^- \rightarrow CO_3^- \]
The Hybrid Fuel-Cell Power Plant

• Control Schemes
  – Power Control
    • By Methane flow rate \( n_{CH_4} \) and stack current \( I^2 \)
    • According to power demand
  – Stack temperature Control
    • By LTR and SSH control moves
    • According to stack temperature setpoints
  – Pressure Control
    • Anode back-pressure control
    • Stack differential pressure control
    • According to constant setpoints
Optimal Reference Governor (ORG)

- The Structure of the ORG
  - Plant Model (state estimator)
  - Operating Windows
  - Multiobjective Optimization Module (MOM)
Optimal Reference Governor (ORG)

• The Structure of the ORG (Cont.)
  – Input
    • Power load demand from central dispatch center
  – Outputs
    • Six setpoints or feedforward controls to be optimized
      – Stack current density: $I^2$
      – Methane flow rate: $n_{\mathrm{CH}_4}$
      – Turbine speed: $\text{RPM}$
      – SSH power: $Q_{\text{SSH}}$
      – LTR control move: $u_{\text{LTR}}$
      – AGO control move: $u_{\text{AGO}}$
Optimal Reference Governor (ORG)

- The Structure of the ORG (Cont.)
  - Search mode
    - Candidate setpoints go to the state estimator
    - The state estimator approximates the behavior of the plant
    - MOM evaluates the objective and refines the solution
    - Executed periodically or load demand changed
    - Switch to run mode after several iterations
  - Run mode
    - Optimized setpoints go to the actual plant
    - Serve as the references for the local control scheme
The Mathematical Model

• A State Estimator
  – Evaluates the candidate setpoints
  – Estimates the plant output based on given setpoints

• Nomenclature
  – Gas components: \( S = \{H_2, CH_4, CO, CO_2, H_2O, N_2, O_2\} \)
  – Mole fractions: \( x_K \) and \( x_K^{in} \)
  – Mole flow rate: \( N_K^{in} \)
  – Stored gas: \( n_K \)
  – Reaction rates: \( R_{K,j} \) and \( R_{K,j}^{(i)} \)
  – Stack temp. and heat capacity: \( T_S \) and \( C_S \)
  – Enthalpies of I/O flows: \( H_K^{in} \) and \( H_K^{out} \)
  – Where \( K \in \{A, C\} \) \( A: \) anode ; \( C: \) cathode
The Mathematical Model (Cont.)

- **Components Balances**
  - Dynamic equations

\[
\dot{x}_K = \frac{1}{n_K} \left[ N_{K}^{in} (x_{K}^{in} - x_{K}) - x_{K} \sum_{j=1}^{7} \sum_{i=1}^{7} R_{K,j}^{(i)} + \sum_{j} R_{K,j} \right]
\]

- **Energy Balances**
  - Dynamic equations

\[
\dot{T}_S = \frac{1}{C_S} \left[ N_{A}^{in} (H_{A}^{in} - H_{A}^{out}) - H_{A}^{out} \sum_{j=1}^{7} \sum_{i=1}^{7} R_{A,j}^{(i)} + N_{C}^{in} (H_{C}^{in} - H_{C}^{out}) - H_{C}^{out} \sum_{i=1}^{7} R_{C}^{(i)} - P_S - Q_{loss} \right]
\]

- where \(P_S\): stack electric power; \(Q_{loss}\): heat loss
The Mathematical Model (Cont.)

• The Turbine Model
  – Mechanical model:
    \[ J \frac{d\omega}{dt} = \tau_T - \tau_C - \tau_G \]
  – Thermomechanical model:
    \[ \tau_{T,C} = \frac{N_{T,C} \left( H_{T,C}^{\text{out}} - H_{T,C}^{\text{in}} \right)}{\omega} \]
  – Electrical model:
    \[ \tau_G = K_m I_G, \quad v_G = K_e \omega \]
  – where
    \[ J \] : the inertia of the linked mechanical system;
    \[ \omega \] : the angular speed of the rotation of the shaft;
    \[ \tau_{T,C,G} \] : the torques of turbine, compressor, and generator;
    \[ v_G, I_G \] : voltage and current of the equivalent DC generator;
    \[ K_m, K_e \] : armature and motor constant of the generator.
Operating Windows

• The solution space for optimization algorithms
  – Providing search ranges for the six setpoints

• Physically realizable operating ranges
  – Split ratio of control valves
  – Power limit of electrical heater

• To determine operating windows
  – Theoretical analysis
  – Simulation
Operating Windows (Cont.)

- Simulation of the mathematical model
  - With designed inputs
  - Simulation results are plotted against power demand

![Graphs showing various parameters against power demand.](image-url)
Multiobjective Optimization Module

• The core optimizer of the ORG
• Modern heuristic optimizations in power systems
• The Particle Swarm Optimization (PSO)
  – Simulation of bird flocks
  – Population based heuristic algorithm
  – Fast convergence in large-scale nonlinear problems
  – Extension to multi-objective problems
    • Weighted aggregation
    • Pareto theory
Problem Formulation

• Objective Functions
  – Power tracking
  – Temperature tracking
  – Efficiency

• States Estimation
  – The mathematical model serves as a state estimator

\[ F_1 = \sum_{i=1}^{N} (P_{load} - P_{net})^2 \]
\[ F_2 = \sum_{i=1}^{N} (TCI_{set} - TCI_{act})^2 \]
\[ F_3 = \sum_{i=1}^{N} \frac{P_{csm}}{P_{net}} \]

\[ [P_{net} \ TCI_{act}] = f_{estimator}(I^2, n_{CH_4}, RPM, Q_{SSH}, u_{LTR}, u_{AGO}) \]

– $P_{net}$ and $TCI_{act}$ are used to evaluate objective functions
Problem Formulation (Cont.)

• The optimization Problem
  – Search for the six setpoints
    \{ I_2 \ n_{CH_4} \ RPM \ Q_{SSH} \ u_{LTR} \ u_{AGO} \}
  to minimize \{ F_1 \ F_2 \ F_3 \}

• Constraints
  – Each setpoint searched by the MOM must belong to its operating window
Optimization Results

• MOPSO with Pareto Theory
  – Test power load = 250 kW
  – 12 candidate solutions and their projections
Optimization Results (Cont.)

- **Weighted Aggregation**
  - Need additional knowledge to select weights
  - Weights are determined by specific requirements
  - Without losing generality, select
    \[ F = 0.4F_1 + 0.4F_2 + 0.2F_3 \]
  - Test power load: 150 kW – 300 kW with 5 kW increment
Optimization Results (Cont.)

• **Weighted Aggregation**
  – Solutions: optimized setpoints

![Graphs showing optimization results for various parameters: Current Density, Methane Flow Rate, Rotational Speed, SSH Power, LTR Control Move, AGO Control Move, and Power Demand.](image-url)
Optimization Results (Cont.)

- **Weighted Aggregation**
  - System response with the optimized setpoints

- **DFC DC Power**
  - [Graph showing DFC DC Power]

- **Turbine AC Power**
  - [Graph showing Turbine AC Power]

- **DFC/T Net Power**
  - [Graph showing DFC/T Net Power]

- **Overall Plant Efficiency**
  - [Graph showing Overall Plant Efficiency with Sim. w / ORG and Exp. w/o ORG]

- **Stack Temperature**
  - [Graph showing Stack Temperature]

- **Cathode Inlet Temperature**
  - [Graph showing Cathode Inlet Temperature with Sim. w / ORG and Setpoints]
Conclusion

• The DFC/T Power Plant
  – An alternative power source for DG
  – Advantages

• ORG for the DFC/T Power Plant
  – Generate optimal setpoints to improve efficiency
  – Advance heuristic optimization algorithms
  – A mathematical model serves as a state estimator

• An Optimization Framework
  – A nonlinear multi-objective optimization framework
  – Capable of other types of power plants
Thank you!

• Questions?
Algorithms for the MOM

• Modern Heuristic Optimizations
  – Genetic algorithms
  – Particle swarm optimization
  – Evolution strategies and evolutionary programming
  – Simulated annealing
  – Selected PSO as the first attempt
    • Fast convergence on large-scale problems
    • Wide applications in power systems
    • Low implementation complexity
PSO Algorithm

- **Step 1:** Initialize $x_i^1$ and $v_i^1$ for all $i$. Usually take $x_{i,j}^1 \in$ operating window.

- **Step 2:** Let the private best, $p_{best_i} = x_i^1$

- **Step 3:** For each particle, do
  - Create random vectors $r_1$ and $r_2$, by taking $r_{1,j}, r_{2,j} \in U[0,1]
  - Update the particle velocities:
    \[ v_{i}^{k+1} = w v_i^k + c_1 r_1 \odot (g_{best} - x_i^k) + c_2 r_2 \odot (p_{best_i} - x_i^k) \]
  - Update the particle positions:
    \[ x_{i}^{k+1} = x_i^k + v_i^k \]
  - Update the private best: if $f(x_{i}^{k+1}) < f(p_{best_i})$, then $p_{best_i} = x_{i}^{k+1}$
  - Update the global best: if $f(x_{i}^{k+1}) < f(g_{best})$, then $g_{best} = x_{i}^{k+1}$

- **Step 4:** If converged, stop iteration, and $g_{best}$ is the optimal solution of the problem. Otherwise, $k = k+1$, go to step 3.
PSO Parameters

– Dimension: 6
– # of particles: 2000
– Max. # of iteration: 100
– \( w = 0.9 \) to 0.4
– \( C_1 = C_2 = 0.3 \)
Pareto Theory

- To solve multiobjective optimization problems
- Pareto dominance
  - $A$ dominates $B$ (or $B$ is dominated by $A$), if
    - all criteria of $B$ are no better than $A$, and
    - at least one criterion of $A$ is strictly better than $B$.
  - $A$ dominates $B$ means $A$ is absolutely better than $B$.
- Pareto based MOPSO
  - Keep a repository of particles that are nondominated by any other particles
  - Use the repository as the *global best* to lead the search
Realization of State Estimator

• Mathematical model
  – Based on analytical analysis (mass and energy conservations)
  – Continuous state model realized by differential equations
  – Accurate but computationally expensive

• Neural network model (future work)
  – Trained by operational data
  – Discrete state model
  – Nonlinear approximator
  – Computationally efficient