System Modeling and Online Optimal Management of MicroGrid Using Mesh Adaptive Direct Search

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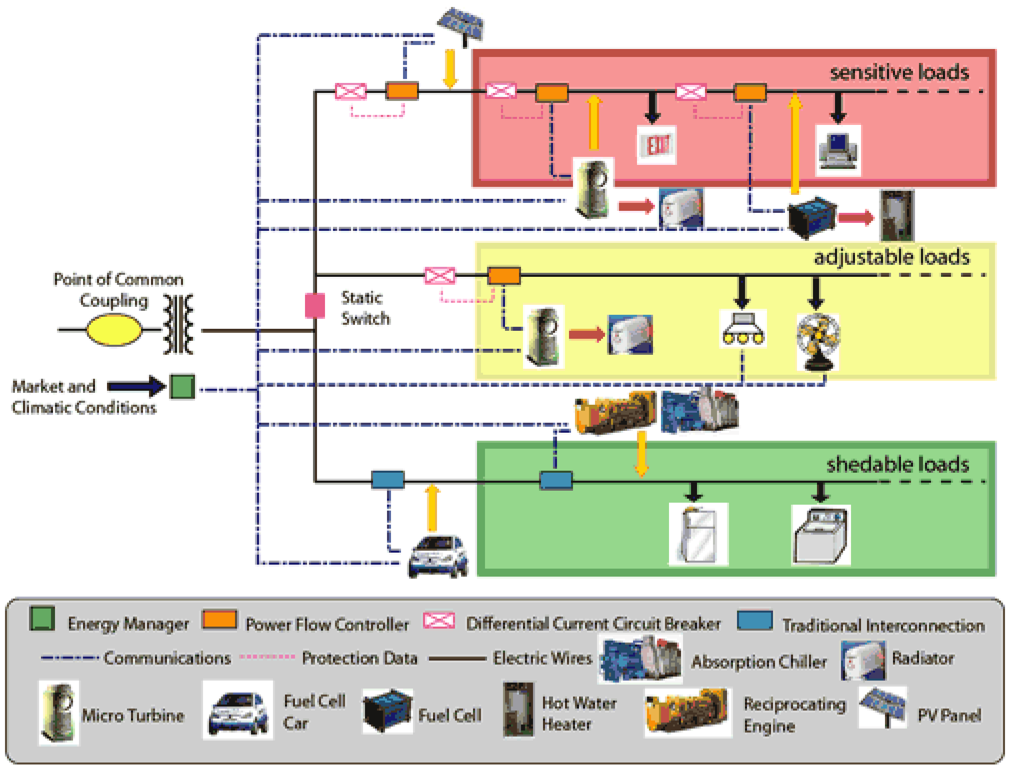
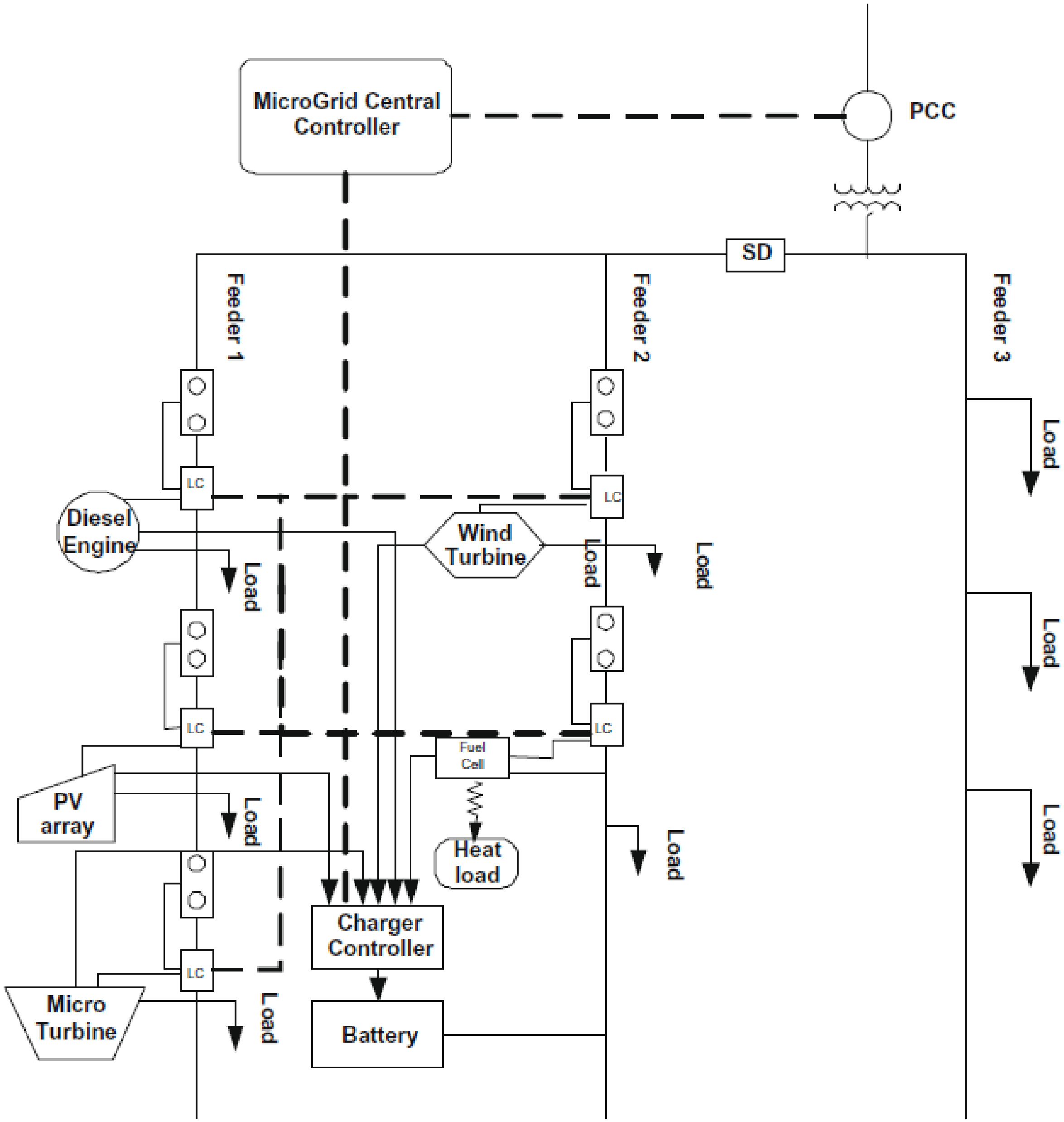
Overview

- MicroGrids
- Optimization Model
- Mesh Adaptive Direct Search
- Sequential Quadratic Programming
- Simulation/Experiment
- Conclusions

MicroGrids

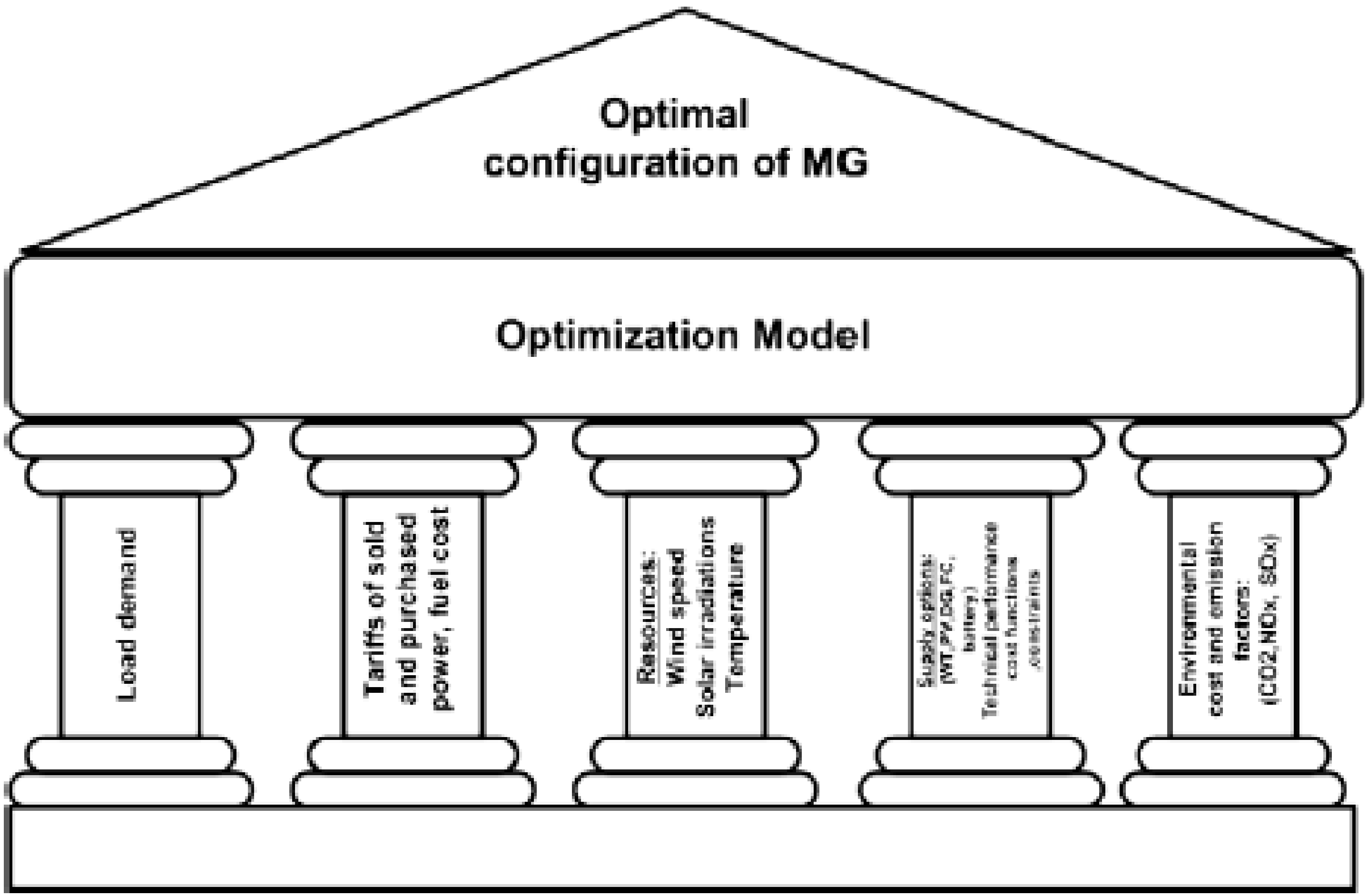
- Subsystem that be connected or disconnected to the main power grid
- Many Potential Benefits





MicroGrid Central Controller
PCC
SD
Feeder 1
Feeder 2
Feeder 3
LC
Diesel Engine
Wind Turbine
Load
Fuel Cell
Heat load
PV array
Charger Controller
Battery
Micro Turbine

Optimization Model



Components for Optimization

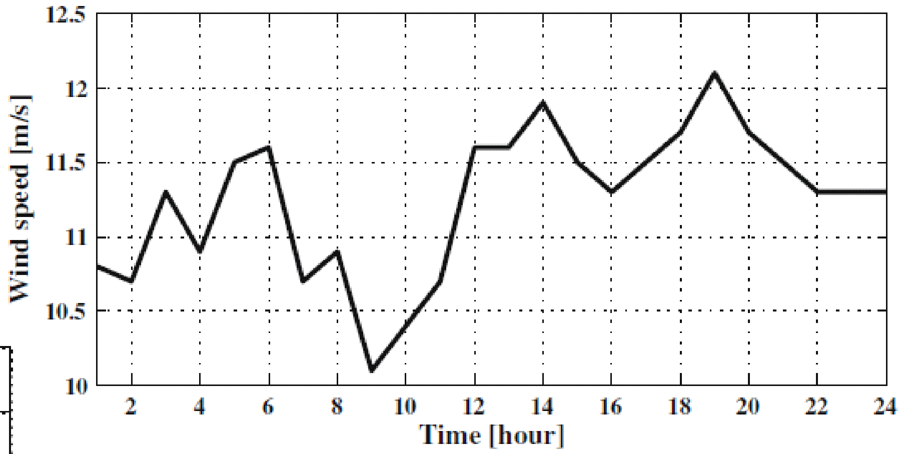
- Minimize:
  - Cost
  - Emissions
- Optimize:
  - Satisfaction of load demand
  - Use of resources

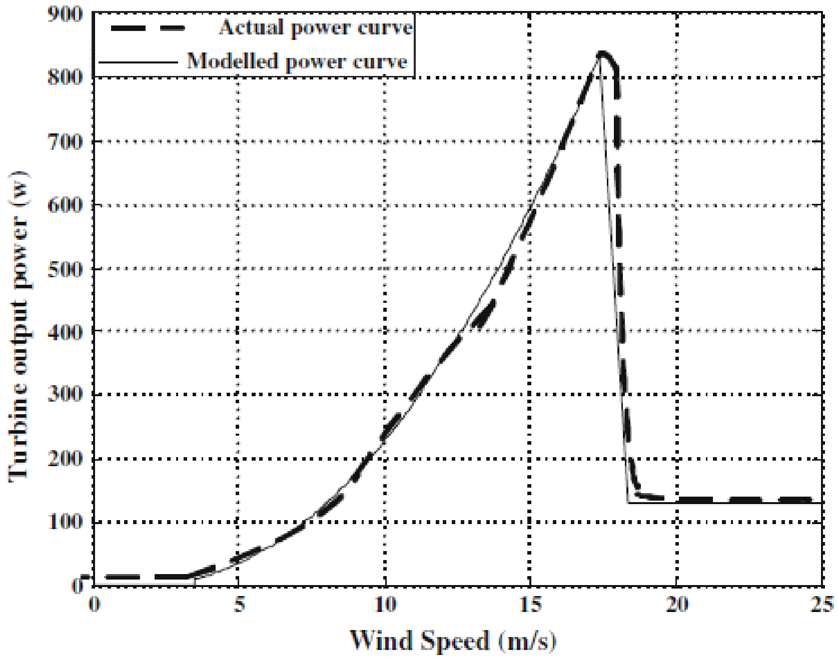
Available Data for Optimization

- Power Demand
- Solar Irradiation
- Temperature
- Wind Speed
- Fuel Costs
- Purchase and Selling Tariffs
- Startup Costs
- Maintenance Costs
- Operating Costs
- Economic Performance
- Technical Performance
- Emission Performance

Wind Turbine

- Power is a function of wind velocity

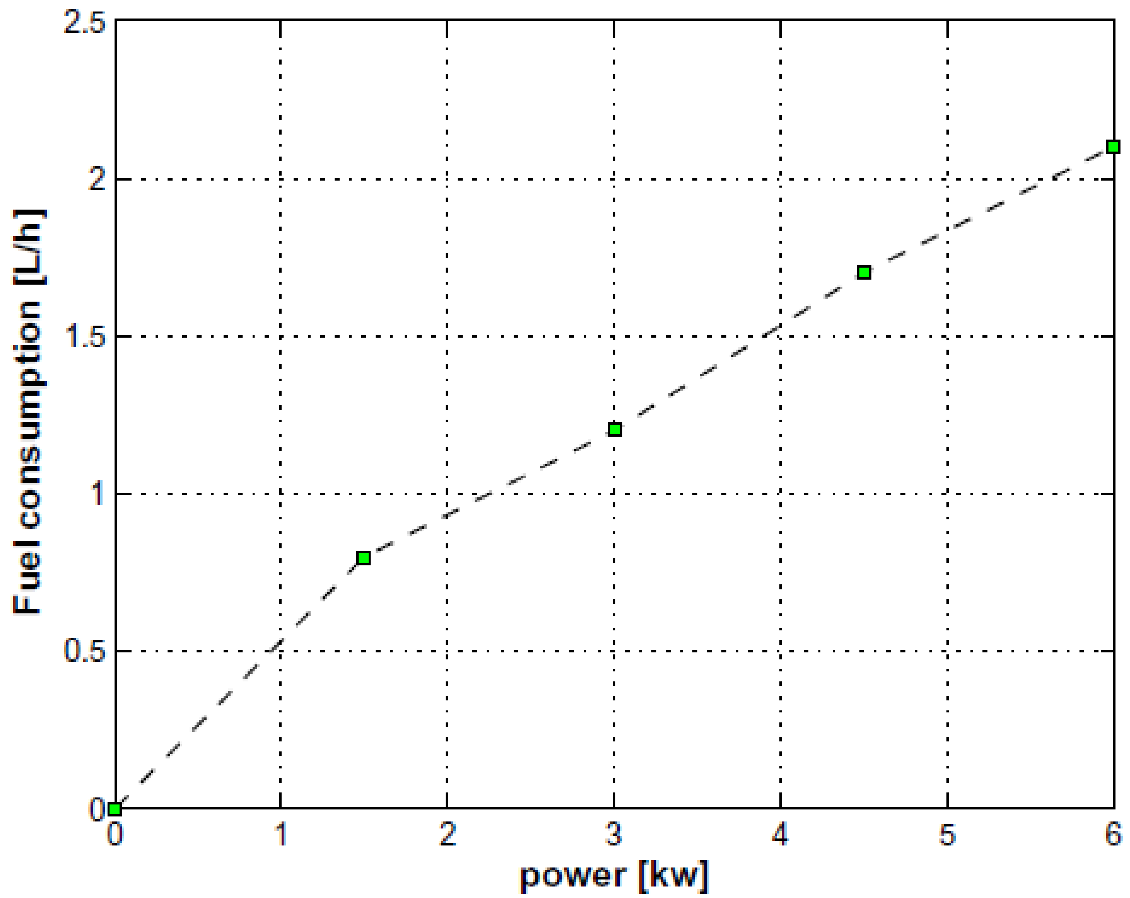




Photovoltaic Cells

- Power produced is a function of:
  - Model's Maximum Power
  - Incident Irradiance
  - Temperature
- Assumptions for Simulated Model:
  - Peak power= 83W
  - Voltage at Peak Power= 17.1V
  - Current at Peak Power 4.84A

Diesel Generator

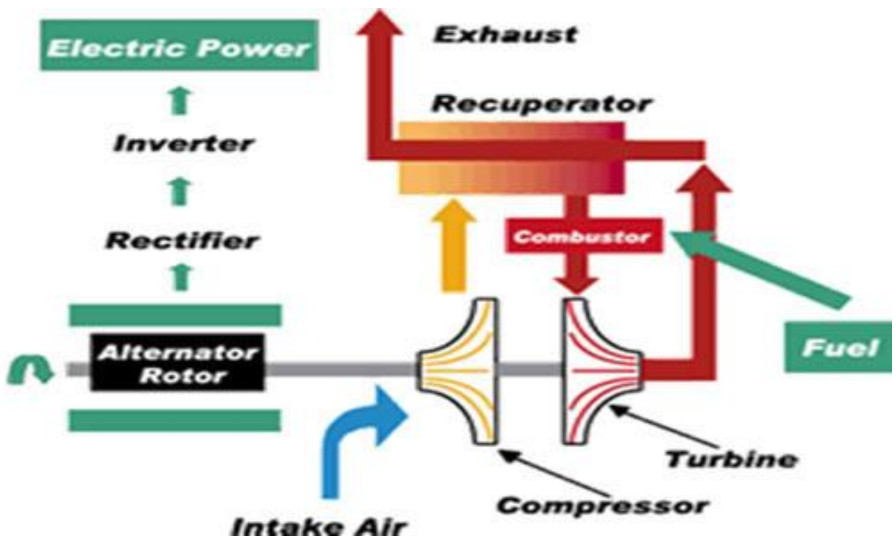


Fuel Cells

- Hydrogen and Oxygen are combined to produce electricity, heat, and water
- Natural gas is used to supply the fuel cell

Microturbine

- Efficiency is increased as more power is supplied
- Natural gas is the fuel supply



Battery Storage

- Energy can be stored and released
- The battery should not be discharged below 20%
- Assume that the maximum charge is 90% of what is capable

Emissions

- Nitrogen Oxides, Sulfur Oxides, and Carbon Oxides are aimed to be minimized

Externality costs and emission factors for NO_x, SO_2, and CO_2.

Emission type	Externality costs ($/lb)	Emission factors for DE (lb/MW h)	Emission factors for FC (lb/MW h)	Emission factors for MT (lb/MW h)
NO_x	4.2	21.8	0.03	0.44
SO_2	0.99	0.454	0.006	0.008
CO_2	0.014	1.432	1.078	1.596

Cost Function

For generating unit I

P_i = Decision variables for power

M=Emission Type

N=number of generating units

$$CF(\boldsymbol{P}) = \sum_{i=1}^{N}(C_i \times F_i(P_i) + OM_i(P_i) + STC_i + DCPE_i - IPSE_i) + \sum_{i=1}^{N}\sum_{k=1}^{M}\alpha_k(EF_{ik}P_i)$$

Fuel cost

Fuel consumption rate

Operation and maintenance cost

Startup costs

Daily Purchase Cost

Daily income

External cost for emission type k

Emission factor

Decision Variables

$$P_i = P_{FC_i}, P_j = P_{MT_j}, P_k = P_{DG_k} : i = 1, \dots, N_1; j = N_1 + 1, \dots, N_2; k = N_2+1,\dots,N$$

Fuel Cell

Microturbine

Diesel Generator

Power Balance Constraint

$$\sum_{i=1}^{N} P_i - P_L + (P_{PV} + P_{WT} + P_{batt}) = 0$$

Photovoltaic cell

Wind turbine

Battery storage

Direct Search

- Only function values
- No knowledge of the internal structure of problem is needed
- Can easily and quickly adapt
- Can find solutions even when noise is present or the function is undetermined at some points

Mesh Adaptive Search Algorithm

- Generalization of pattern search algorithm
- Derivative free
- Iterative process of two steps
  - Search Step
  - Poll Step

[0] **Initializations**

$x_0 \in X$, $\Delta_0 \in \mathbb{R}^+$
$k \leftarrow 0$

[1] **Poll and search steps**

Search step

evaluate the functions on a finite number of points of $M(k, \Delta_k)$

Poll step

compute p MADS directions $D_k \in \mathbb{R}^{n \times p}$
construct the frame $P_k \subseteq M(k, \Delta_k)$ with x_k, D_k, and Δ_k
evaluate the functions on the p points of P_k

[2] **Updates**

determine the type of success of iteration k
solution update (x_{k+1})
mesh update (Δ_{k+1})
$k \leftarrow k + 1$
check the stopping conditions, **goto** [1]

Search Step

- All trial points lie on the mesh

$$M(k, \Delta_k) = \bigcup_{x \in V_k} \{x + \Delta_k D z : z \in \mathbb{N}^{n_D}\} \subset \mathbb{R}^n$$

- Any search strategy can be used
- Points can either be rejected when they do not satisfy constraints or the constraints can be removed using the barrier approach

Poll Step

- At 2n trial mesh points near the solution are evaluated
- Based on the result
  - If no better neighbor is found
    - Mesh is refined(aka gets finer)
  - If better neighbor is found
    - Mesh is kept the same or gets courser

Handling of Constraints

- This is the main difference to pattern search
- Utilize the barrier approach

$$CF_X = \begin{cases} CF(\mathbf{P}) & \text{if } \mathbf{P} \in X \\ +\infty & \text{otherwise} \end{cases}$$

- Allows the algorithm to be applied to an “unconstrained” problem

Sequential Quadratic Programming

- SQP is to model this problem at the current point x_k by a quadratic subproblem and to use the solution of this subproblem to find the new point x_{k+1}
- Lagrangian operations, Jacobian operations, and Newton's Methods need to be applied to solve

A line search SQP algorithm:

1. Choose parameters $0 < \eta < 0.5$, $0 < \tau < 1$ and the initial point (x_0, λ_0).
2. Initialize the Hessian estimate, say $B_0 = I$.
3. Evaluate f_0, g_0, c_0 and A_0.
4. Begin major iteration loop in k:
   - 4.1 If termination criteria are met, then stop.
   - 4.2 Compute p_k by solving (3).
   - 4.3 Choose μ_k such that p_k is a descent direction for ϕ at x_k.
   - 4.4 Set $\alpha_k = 1$.
     - i. While $\phi(x_k + \alpha_k p_k, \mu_k) > \phi(x_k, \mu_k) + \eta \alpha_k D\phi(x_k, p_k)$
     - ii. Set $\alpha_k = \tau_\alpha \alpha_k$ for some $0 < \tau_\alpha < \tau$.
   - 4.5 Set $x_{k+1} = x_k + \alpha_k p_k$.
   - 4.6 Evaluate f_{k+1}, g_{k+1}, c_{k+1} and A_{k+1}.
   - 4.7 Compute λ_{k+1} by solving

$$\lambda_{k+1} = -\left[A_{k+1} A_{k+1}^T\right]^{-1} A_{k+1} g_{k+1}$$

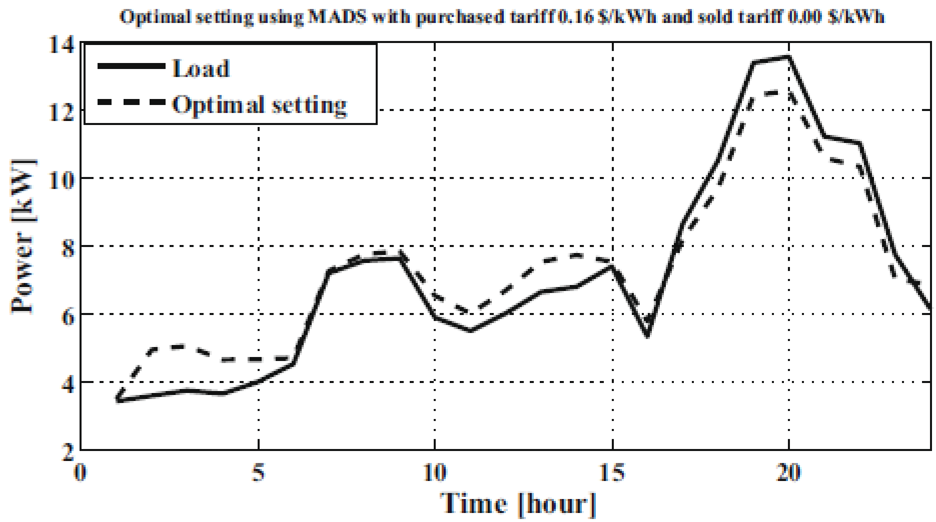
   - 4.8 Set $s_k = \alpha_k p_k$, $y_k = \nabla_x \mathcal{L}(x_{k+1}, \lambda_{k+1}) - \nabla_x \mathcal{L}(x_k, \lambda_{k+1})$.
   - 4.9 Obtain B_{k+1} by updating B_k using a quasi-Newton formula.
5. End major iteration loop.

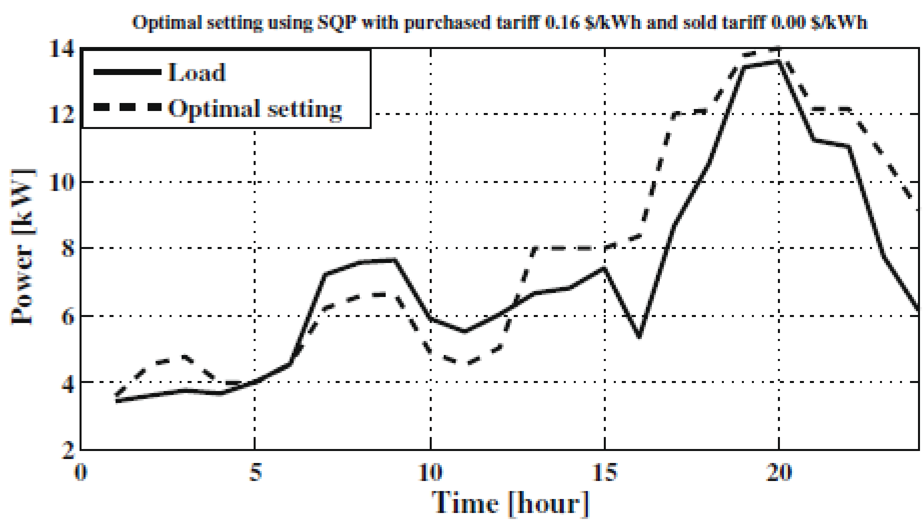
http://acdl.mit.edu/mdo/mdo_06/SQPMethods.pdf

Simulation and Results

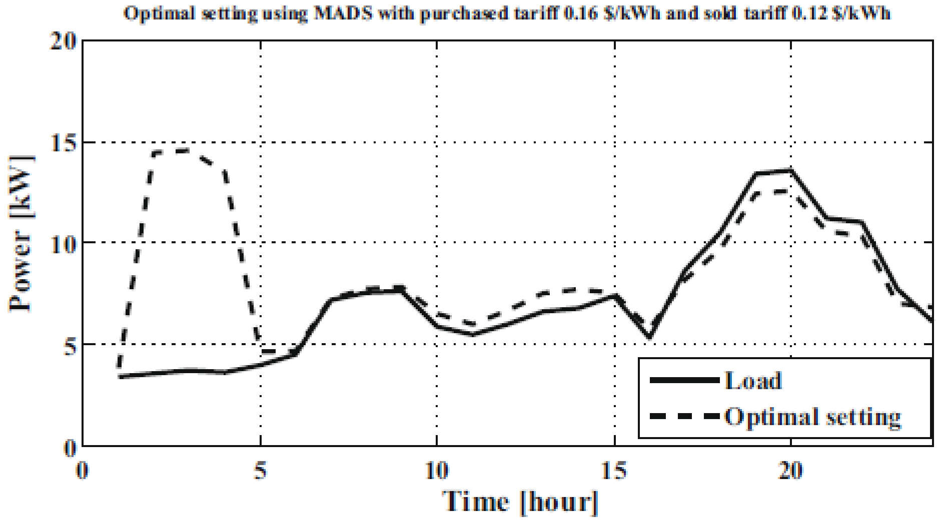
- The model was evaluated with the MADS and SQP methods
- Tariffs were the variable that was changed
- The allowance for selling excess power was a variable considered

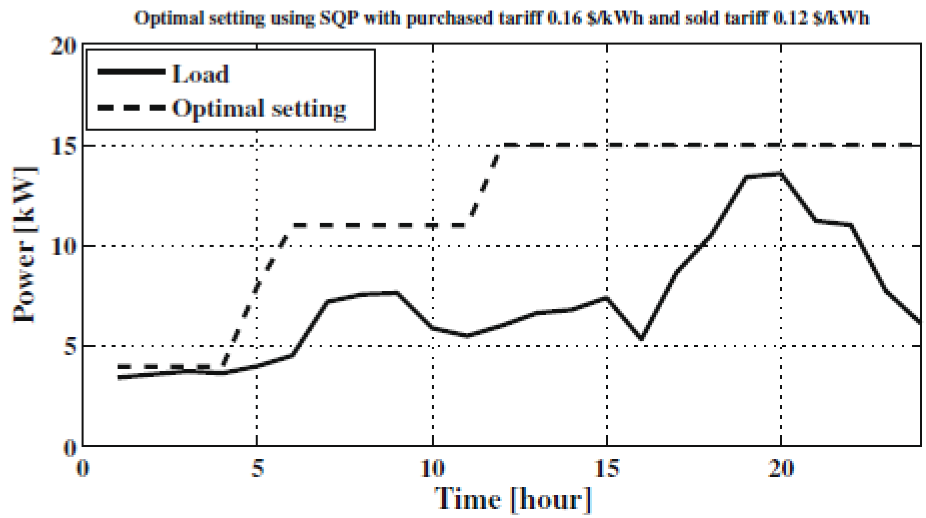
Purchase Tariff= 0.16$/kWh
Sold Tariff= 0$/kWh





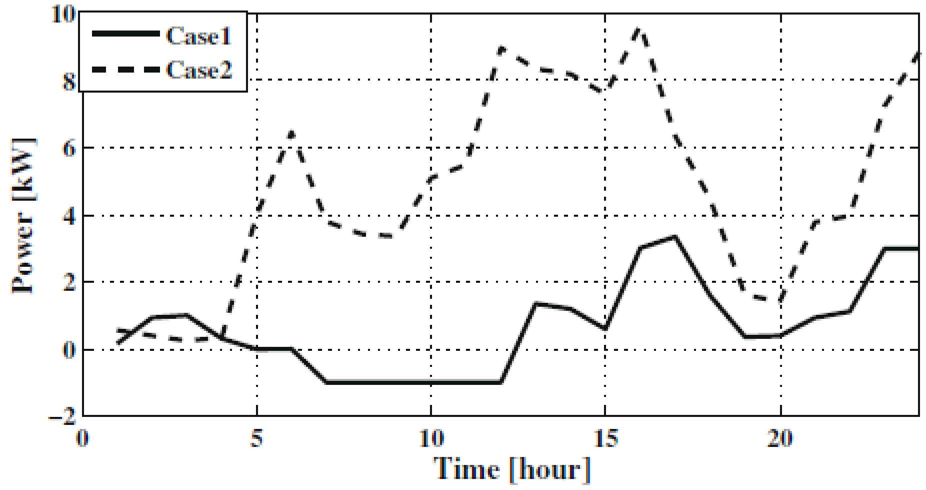
Purchase Tariff = 0.16$/kWh
Sold Tariff = 0.12$/kWh



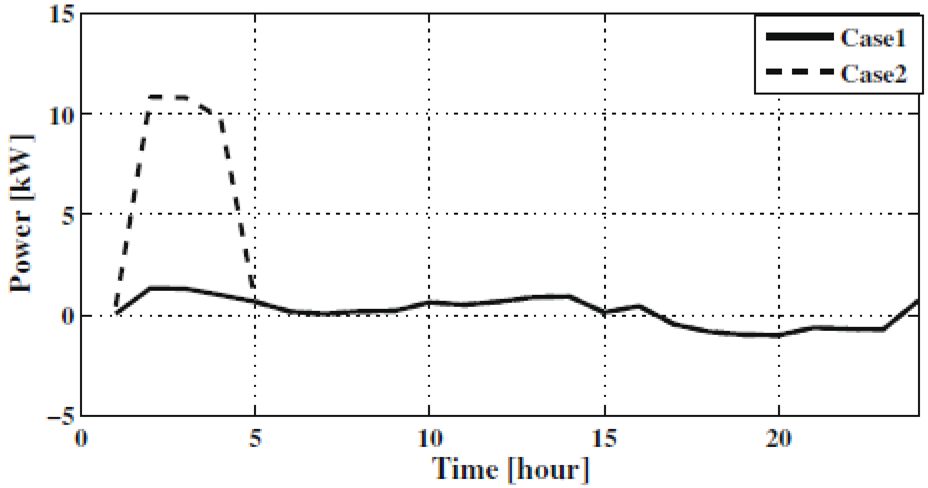


Case Study

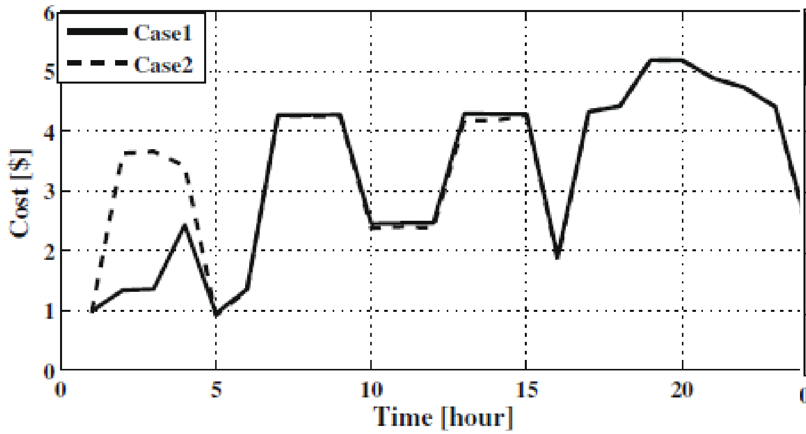
- Case 1:
  - No power sold back
  - Power purchased at 0.16$/kWh
- Case 2:
  - Excess power sold back at 0.12$/kWh
  - Power purchased at 0/16$/kWh



Sold and purchased power using SQP method.



Sold and purchased power using MADS method.



'ig. 15. Cost per day MADS method.

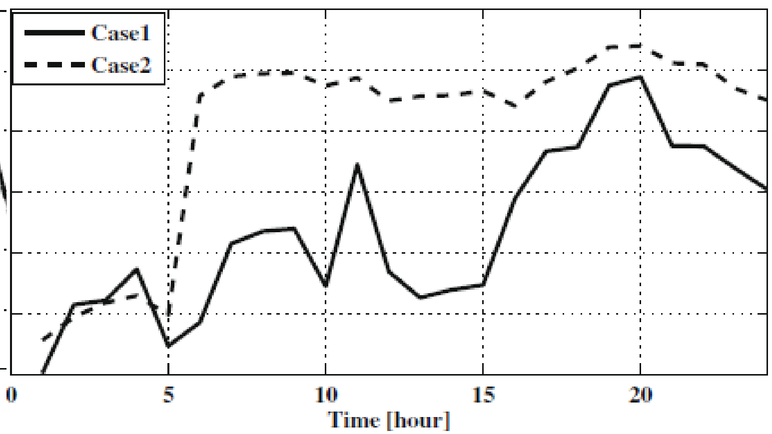
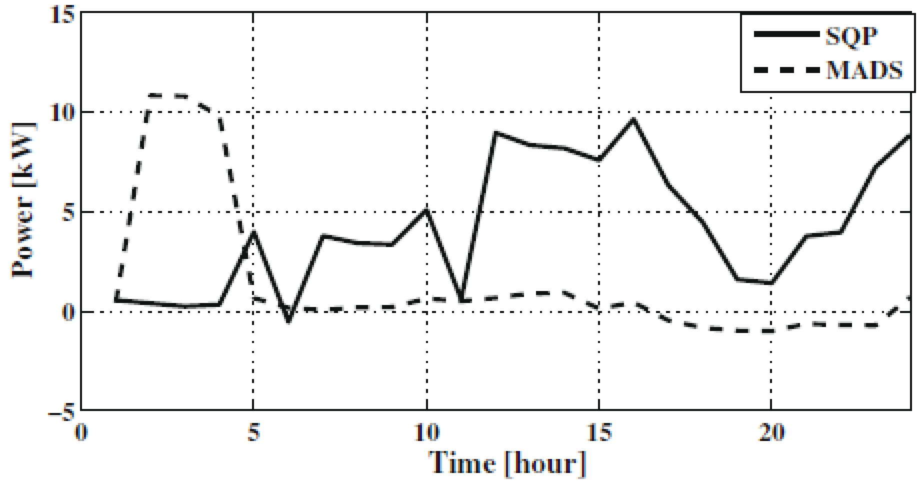
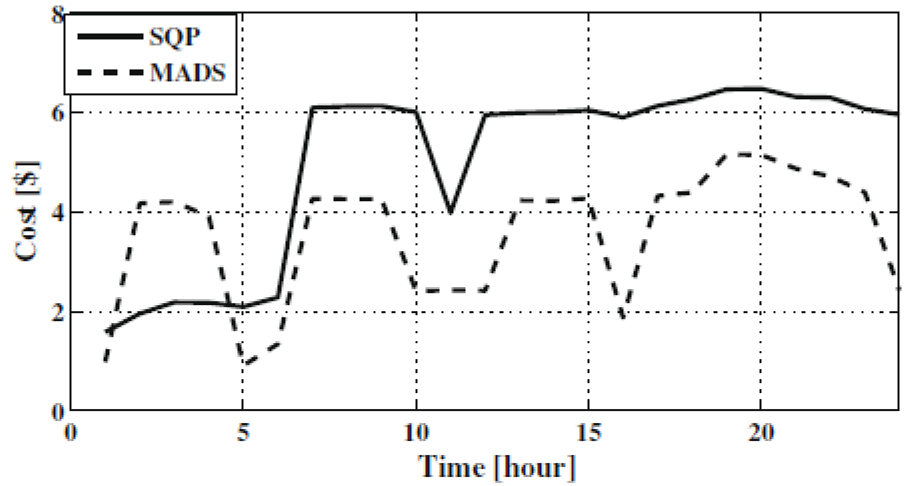


Fig. 16. Cost per day using SQP method.

Comparing Methods



. Sold and purchased power using SQP and MADS methods.



Total cost per day using SQP and MADS methods.

Numeric View

Total optimal generation and total cost of the MG.

	P_L (kW/Day)	C_p ($/kW h)	C_s ($/kW h)	Total cost ($/Day)		Optimal generation (kW/Day)	
				SQP	MADS	SQP	MADS
Case 1	171.4009	0.16	0.00	80.8576	79.0752	187.6473	176.1020
Case 2	171.4009	0.16	0.12	120.8424	83.9106	285.0000	204.2817
Case 3	171.4009	0.12	0.07	120.5106	85.6072	273.1226	204.2817
Case 4	171.4009	0.16	0.07	120.5220	85.7750	273.1226	204.2817

Conclusions

- MADS is a better method for optimizing then SQP
  - Finds the compromise between sold and purchased power
- MADS is a mathematically simpler approach to complex optimization problems
- Some constraints ended up not being active when MADS was applied
- The lowest total cost per day achieved in all cases was found using MADS

References

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Questions