


Lecture Series on
Intelligent Control

Lecture 30
Artificial Bee Colony Algorithm
Optimal Scheduling

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1




**Optimal Scheduling of Distributed
 Energy Resources by Modern Heuristic
 Optimization Technique**

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2



Outlines

- Motivations
- Problem Formulation
- Artificial Bee Colony
- Case Studies
- Summary&Conclusion

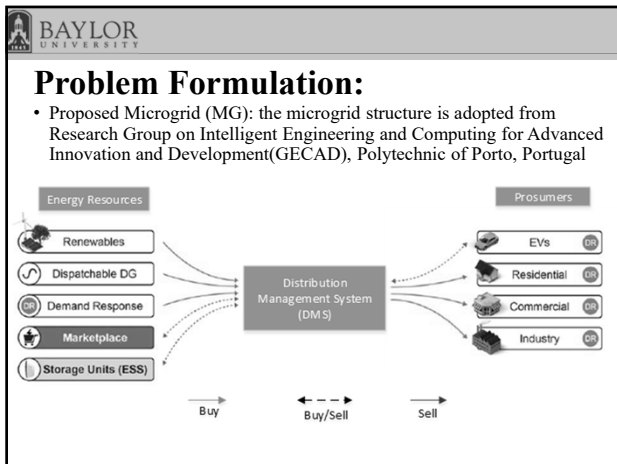
3

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Motivation:

- The increasing number and types of distributed energy resources and prosumers has made the optimal scheduling greatly complicated.
- Hard-to-solve or even impossible-to-solve (either very time consuming or not able to converge) for traditional mathematical methods.
- Modern heuristic techniques have proven their ability to solve complex non-linear, non-convex and large-size optimization problems.

4



5


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- Three major components: energy resources (ER), Distribution management system (DMS), prosumers

Energy Resources	DMS	Prosumers
Renewables	Control and monitor microgrid; perform optimal scheduling.	EVs
Dispatchable DG		Residential
Demand Response		Commercial
Marketplace		Industry
Storage Units(ESS)		

- note: some components are capable of buying/selling electricity from/to MG, such as marketplace, ESS, and EVs.

6

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- Objective function: maximize profit, which is to minimize the operational cost (OC) minus income(IN)

$$\min Z = OC - IN$$

$$IN = \sum_{t=1}^T \left\{ \sum_{L=1}^{N_L} P_{Load(L,t)} \cdot MP_{Load(L,t)} + \sum_{M=1}^{N_M} P_{Sell(M,t)} \cdot MP_{Sell(M,t)} + \sum_{E=1}^{N_E} P_{Cha(E,t)} \cdot MP_{Cha(E,t)} + \sum_{V=1}^{N_V} P_{Cha(V,t)} \cdot MP_{Cha(V,t)} \right\}$$


- IN consists of the electricity selling to consumers, to the electricity market, the revenue from the ESS by charging electricity and from the charging of EVs

7

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- $MP_{Load(L,t)}$ -- the price (\$) of load L in period t ,
- $MP_{Sell(M,t)}$ -- the price (\$) that market M pays in time period t ,
- $MP_{Charge(E,t)}$ -- the price (\$) for the charge process of ESS E in period t ,
- $MP_{Charge(V,t)}$ -- the price (\$) for the charge process of EV V in period t ,
- $P_{Cha(E,t)}$ -- the real power charge (MW) of ESS E in period t ,
- $P_{Cha(V,t)}$ -- the real power charge (MW) of EV V in period t ,
- $P_{Load(L,t)}$ -- the real power demand (MW) of load L in period t ,
- $P_{Sell(M,t)}$ -- the real power (MW) sale to market M in period t ,

8

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- OC consists of the generation cost of DGs, external suppliers, discharge of ESS and EVs, demand response program, and penalty on non-supplied demand and penalty on DGs' generation curtailment.

$$OC = \sum_{t=1}^T \left\{ \sum_{DG=1}^{N_{DG}} P_{DG(DG,t)} \cdot C_{DG(DG,t)} + \sum_{S=1}^{N_S} P_{Supp(S,t)} \cdot C_{Supp(S,t)} + \sum_{L=1}^{N_L} P_{LoadDR(L,t)} \cdot C_{LoadDR(L,t)} + \sum_{M=1}^{N_M} P_{Buy(M,t)} \cdot MP_{Buy(M,t)} + \sum_{V=1}^{N_V} P_{Discho(V,t)} \cdot C_{Discho(V,t)} + \sum_{E=1}^{N_E} P_{Discho(E,t)} \cdot C_{Discho(E,t)} + \sum_{L=1}^{N_L} P_{NSD(L,t)} \cdot C_{NSD(L,t)} + \sum_{I=1}^{N_I} P_{GCP(I,t)} \cdot C_{GCP(I,t)} \right\}$$

9

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- $C_{DG(I,t)}$ -- the generation cost (\$) of unit I in t ,
- $C_{Supp(S,t)}$ -- the energy price of external supplier S in t ,
- $C_{LoadDR(L,t)}$ -- the load reduction cost of L in t ,
- $MP_{Buy(M,t)}$ -- the price (\$) that market M charges in time period t ,
- $C_{Discha(E,t)}$ -- the discharging cost of ESS E in t ,
- $C_{Discha(V,t)}$ -- the discharging cost of V in t ,
- $C_{NSD(L,t)}$ -- the non-supplied demand cost of load L in t ,
- $C_{GCP(I,t)}$ -- the curtailment cost of DG unit I in t ;

10

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- subjected to $G(x, u, y) = 0$
 $H(x, u, y) \geq 0$
- u is control variables, x is state variables, y is system parameters

$G(x, u, y) = 0$: power balance at each node. Load flow is calculated by Backward Forward Sweep method.

$H(x, u, y) \geq 0$: voltage and angle limits, DG generation and supplier limits in each period, ESS capacity, ESS charge and discharge rate limits, EVs capacity, EVs trips requirements, EVs charge and discharge efficiency and rate limits.

11

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- Schematic of the 33-bus distribution system

12

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Artificial Bee Colony (ABC)

- Developed by D. Karaboga, a turkish soloar in 2005.
- Motivated by the intelligent behavior of honey bees.
- Easy to implement and control. (less control variables, only the bee size and the probability of updating solution in onlooker bees need to be given)
- Good balance in exploration and exploitation process.

13

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- Artificial Bee Colony (ABC):
Population-based searching algorithm

The diagram illustrates the ABC algorithm with a central 'Hive' box. Three bees are shown: an 'Employed bee' (A) near a 'Food source' (A), an 'Onlooker bee' (C) near a 'Food source' (C), and a 'Scout' (B) near a 'Food source' (B). Arrows indicate the flow of information from food sources to the bees and from the bees to the hive. Text labels define the roles: Employed bee (search for food source, record good food sources, share info), Onlooker bee (search around neighborhood of good food source), and Scout (random search to avoid local minimum). A label 'Food sources: feasible solutions' points to the food sources.

14

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The flowchart shows the process: 'load distribution case database' leads to 'load ABC parameters', which leads to 'ABC code'. The 'ABC code' box has two outputs: 'Fitness value' and 'Radial network power flow'. A text box on the right details the steps: Step 1 (Initialization), Step 2 (Update food sources for employed bees), Step 3 (Update food sources for onlooker bees), Step 4 (Memorize the best solution), and Step 5 (Replace solution for scout bees after maximum trails).

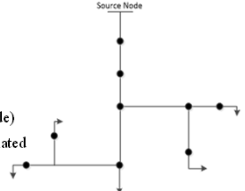
Step 1 Initialization: randomly generate solutions in space.
Step 2 For all employed bees ($i = 1, \dots, SN$): Update food sources (solutions), evaluate all the fitness values and pass the information to onlooker bees
Step 3 For all onlooker bees (only 'good' solutions will be chosen by certain probability p): Update food sources (solutions) with high fitness values
Step 4 Memorize the best solution so far.
Step 5 For all scout bees (will be executed only after maximum trails): Replace solution with a new randomly produced solution and then update the solution to avoid local minimal.

15

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Radial network power flow

- R and X are comparable, therefore Newton method doesn't work properly because Jacobian matrix is ill-formed.
- Backward Forward Sweep (Current method)
- KCL and KVL laws:
 1. Assume terminal voltages are nominal
 2. Backward: calculate previous nodes voltage and line current, till the source node
 3. Forward: update node voltages (except source node) starting from source node (constant) using the calculated current in Backward phase.



16

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Case Studies:

- 33-bus Scenarios with nominal voltage 12.66 kV

Table I. Scenario I Overview

33-bus 12.66kV distribution network
66 DGs
10 External suppliers
1 Large wind turbine
15 ESS
1800 EVs (V2G allowed)
1 Market
32 various loads involved in demand response

17

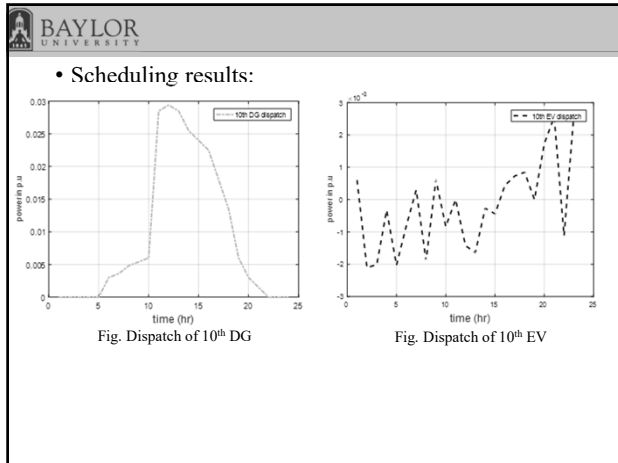
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- The objective of implementing heuristic method to tackle complex optimal scheduling is to obtain satisfying results by significantly reducing computational time, because without transformation of the original problem, conventional solver such as mixed integer nonlinear programming (MINLP) will take hours, even days. Table II demonstrates computational time.

Table II. Execution Time

MINLP	ABC
CPU: Intel (R) Xeon (R) @ 2.10GHZ with 16GB RAM	CPU: Intel (R) i7 @ 3.4GHZ with 8GB RAM
19hours	9.01min
280,729 Equations	234,541 Single variables
	88,380 Discrete variables

18



19

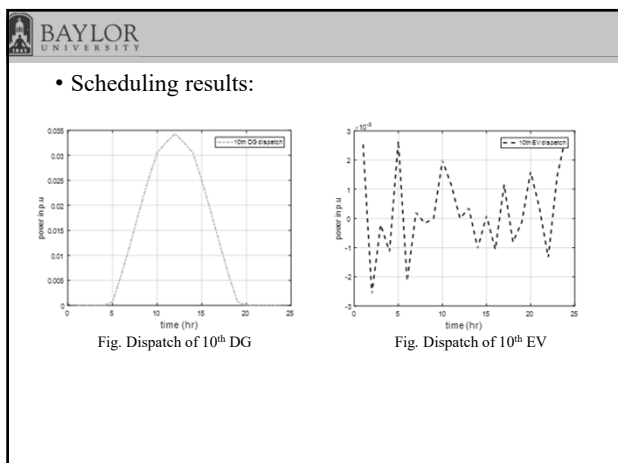
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• 180-bus Scenario


180-bus 30kV distribution network
116 DGs
1 External suppliers
7 ESS
6000 EVs (V2G allowed)
1 Market
90 various loads involved in demand response

MINLP	ABC
CPU: Intel (R) Xeon (R) @ 2.10GHZ with 16GB RAM	CPU: Intel (R) i7 @ 3.4GHZ with 8GB RAM
168hours	18.12min
910,033 Equations	763,033 Single variables
290,568 Discrete variables	

20



21




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Summary&Conclusion:

- A microgrid which consists of DGs, ESS, EVs, market, responsive loads, etc. has been adopted for a comprehensive investigation.
- Such problem is a non-linear and non-convex problem, for which it is hard or impossible to use common optimization tools without modification of the system.
- Modern heuristic method, ABC, is chosen due to its good balance on exploration and exploitation, and ease to implement.
- By using ABC, successful solutions can be obtained and computational time has been reduced significantly.

22



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Questions?

23
