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ALGORITHM: VNS-DEEPSO Combination of Variable Neighborhood Search algorithm (VNS) and Differential Evolutionary Particle Swarm Optimization (DEEPSO)

TEAM: UN-ACCELOGIC-KHALIFA

Cooperation of Universidad Nacional de Colombia (UN), ACCELOGIC and Khalifa University

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Content

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1. Introduction

34 electric vehicles.

7 renewables and traditional energy sources.

Smart grid

2 energy storage systems .

2 markets.

90 controlable loads (demand response).

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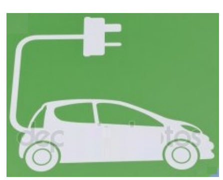
2. Aspects of uncertainty in smart grids

Weather conditions

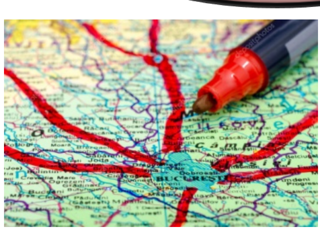
Load forecast

Uncertainty considerations in smar grids

Planned EVs' trips



Market prices



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3. Structure of the problem to solve

Deparameters:
1) Number of population
2)Number of scenarios

Types of variables:
1) Active power and Binary status of a DG
2) EV charging and discharging
3) Loads for demand response
4) ESS charging and discharging
6) Market

Costs
1) Minimize operational costs
2) Energy price of external supplier

Function Variable Neighborhood Search (VNS) and Differential Evolutionary Particle Swarm Optimization (DEEPSO)

Output
1) Penalties
2) SolFitness
3) Number of functions evaluations. Maximum number of evaluations 50,000.

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3. Structure of the problem to solve

Number of functions evaluations

Number of functions evaluations. Maximum number of 50,000	=	Number of scenarios	*	Size of the population to evaluate	*	Number of iterations (generations)

Objective function

Minimize f(x)	=	Minimizing operational costs	-	Maximizing incomes

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4. Heuristic Algorithms Tested.

1. Mean Variance Mapping Optimization (MVMO)

Ranking Index= 20.345

2. Chaotic Biogeography-Based Optimization (CBBO)

Ranking Index= 23.749

3. Variable Neighborhood Search (VNS) Algorithm.

Ranking Index= 19.616

4. Differential Evolutionary Particle Swarm Optimization (DEEPSO) Algorithm.

Ranking Index= 20.361

4. Heuristic Algorithms Tested.

MVMO, CBBO, DEEPSO

- S. **Rivera**, A. Romero, “Dispatch Modeling Incorporating Maneuver Components, Wind Power and Electric Vehicles Penetration, using Heuristic Techniques,” Application of Modern Heuristic Optimization Techniques in Power and Energy Systems, ed: Wiley, in press, **2017**.
- E. Mojica-Nava, S. **Rivera**, N. Quijano. “Game-Theoretic Dispatch Control in Microgrids Considering Network Losses and Renewable DER Integration,” IET Generation, Transmission and Distribution, vol. 11, no. 6, pp. 1583-1590, **2017**.
- W. Mejia, D. Rodríguez, S. **Rivera**, J. Rosero. “Heuristic Estimation of Parameters in High-Frequency Models of Induction Motors for Bearing Currents Simulation,” International Review of Automatic Control (IREACO), vol. 9, no. 6, pp. 355-364, **2016**.
- D. Arango; R. Urrego, S. **Rivera**, “Robust Loss Coefficients: Application to Power Systems with Solar and Wind Energy,” International Journal of Power and Energy Conversion, in press, **2017**.
- D. Alvarez, S. **Rivera**, “Coefficients Estimation of Circuit Model of Transformers Windings Using Heuristic Optimization and Signal Comparison Criteria,” Application of Modern Heuristic Optimization Techniques in Power and Energy Systems, ed: Wiley, in press, **2017**.

VNS Algorithm,

```
% THIS SCRIPT IS BASED ON THE WINNER CODES IN THE TEST BED 2 ON THE
% IEEE 2017 Competition & panel: Evaluating the Performance of Modern Heuristic
% Optimizers on Smart Grid Operation Problems: Variable Neighborhood Search algorithm (VNS)
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5. Algorithm called Variable Neighborhood Search (VNS).

Initialization:

Set of neighborhood structures (Nk) k=1,..,k .
To find an initial solution x.

Repeat:

(a) Set k ⟵1;.
(b) Until k = k_{max}, repeat the following steps:
i. Generate a point x´ at random from the k^{th} neighborhood of x (x´ϵ $N_k(x)$);
ii. Apply some local search method with x´ as initial solution; denote with x´´ the local optimum obtained;
iii. If this local optimum is better than the best solution found in the process, move there (x⟵x´´), and continue the search with *N*1 (k⟵1), otherwise, set k⟵k+1, if k > k_{max} ,
set k ⟵1.

from Vargas Fortes, E., Macedo, L. H., de Araujo, P. B., & Romero, R. (2018). A VNS algorithm for the design of supplementary damping controllers for small-signal stability analysis. *International Journal of Electrical Power & Energy Systems*, *94*, 41-56.

5. Algorithm called Variable Neighborhood Search (VNS).

Variable neighborhood search (VNS),[1] proposed by Mladenović, Hansen, 1997,[2] is a metaheuristic method for solving a set of combinatorial optimization and global optimization problems. It explores distant neighborhoods of the current incumbent solution, and moves from there to a new one if and only if an improvement was made.

from Vargas Fortes, E., Macedo, L. H., de Araujo, P. B., & Romero, R. (2018). A VNS algorithm for the design of supplementary damping controllers for small-signal stability analysis. *International Journal of Electrical Power & Energy Systems*, *94*, 41-56.

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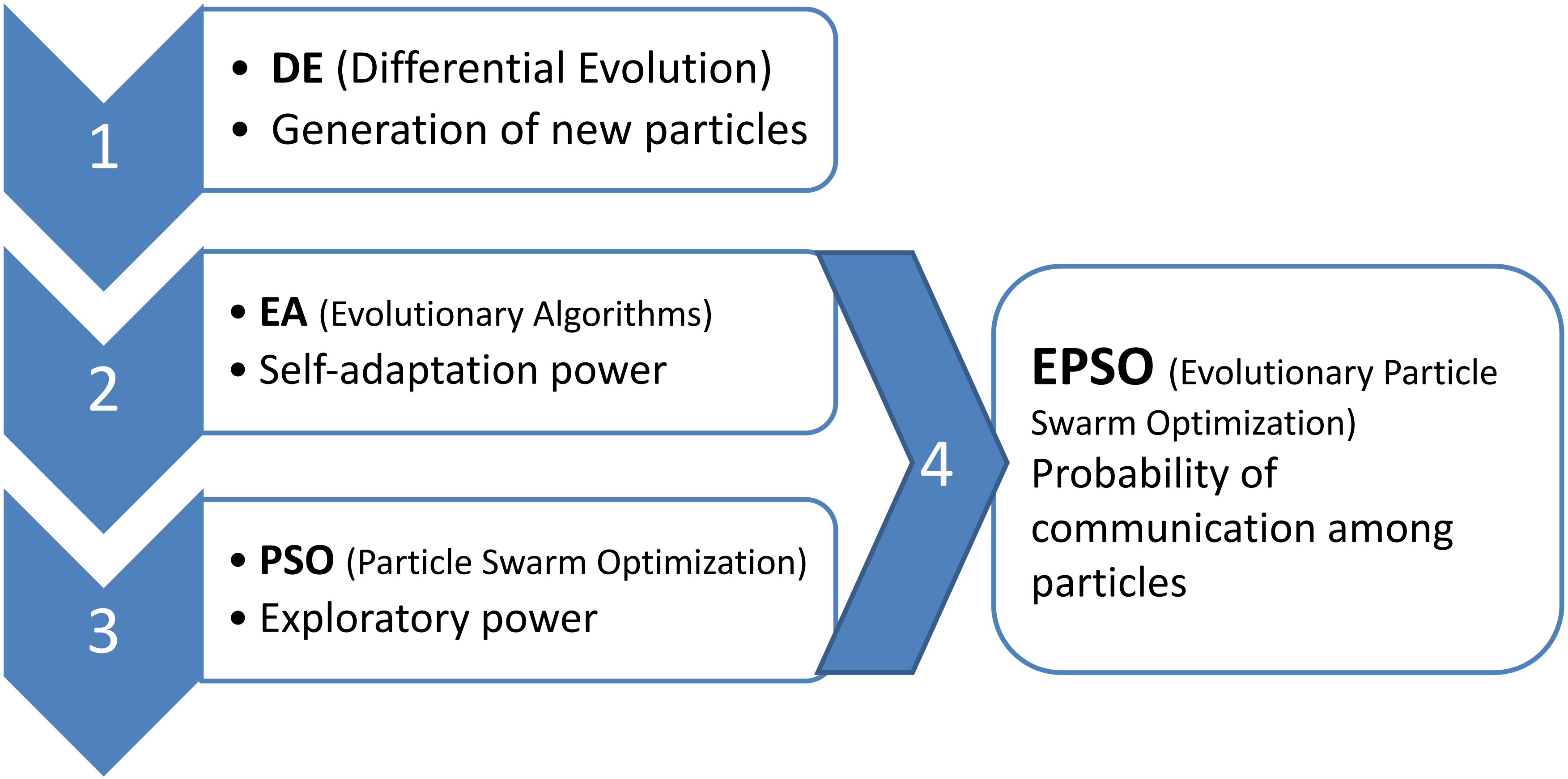
5. Variable Neighborhood Search (VNS).

- Extensively used to solve problems in operations research
- Almost not applied to power systems problems
- Does not require defining parameters
  - Population size
  - Mutation rate
- Does not require tuning the algorithm to every instance of the problem
- Easy to implement and understand

from Vargas Fortes, E., Macedo, L. H., de Araujo, P. B., & Romero, R. (2018). A VNS algorithm for the design of supplementary damping controllers for small-signal stability analysis. *International Journal of Electrical Power & Energy Systems*, *94*, 41-56.

6. Differential Evolutionary Particle Swarm optimization (DEEPSO)



Miranda, V., & Alves, R. (2013, September). Differential evolutionary particle swarm optimization (deepso): A successful hybrid. In *2013 BRICS Congress on Computational Intelligence & 11th Brazilian Congress on Computational Intelligence (BRICS-CCI & CBIC)* (pp. 368-374). IEEE.

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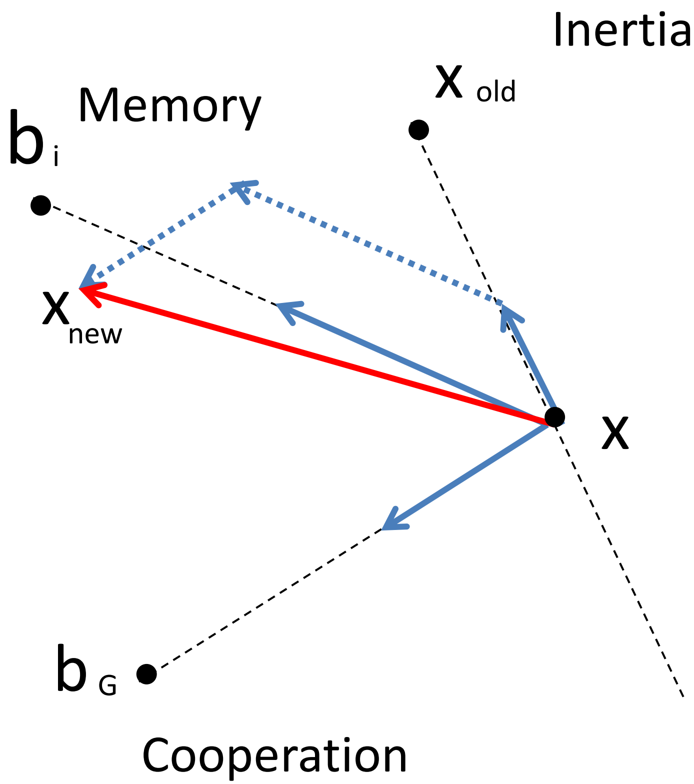
6. Particle Swarm Optimization PSO



1. Direct ancestor
2. The ancestor of its ancestor
3. The past best ancestor
4. The best ancestor found by the swarm

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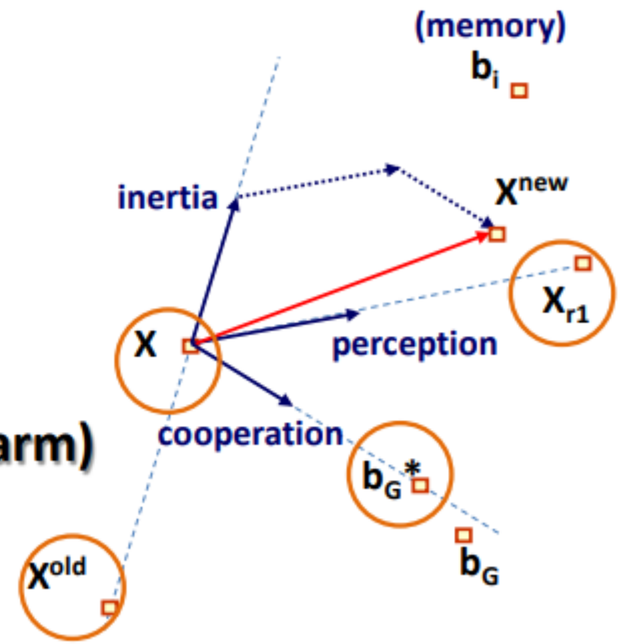
6. DEEPSO

RECOMBINATION via THE MOVEMENT RULE

movement of a particle:

$$X^{new} = X + V^{new}$$

- **inertia:**
  moving in the same direction
- **perception:**
  sensing a local gradient (by the swarm)
- **cooperation:**
  attraction to the proximity of the global best



$$V^{new} = w_I^* V + w_M^* (X_{r1} - X) + w_C^* \, P \, (b_G^* - X)$$

Miranda, V., & Alves, R. (2013, September). Differential evolutionary particle swarm optimization (deepso): A successful hybrid. In *2013 BRICS Congress on Computational Intelligence & 11th Brazilian Congress on Computational Intelligence (BRICS-CCI & CBIC)* (pp. 368-374). IEEE.

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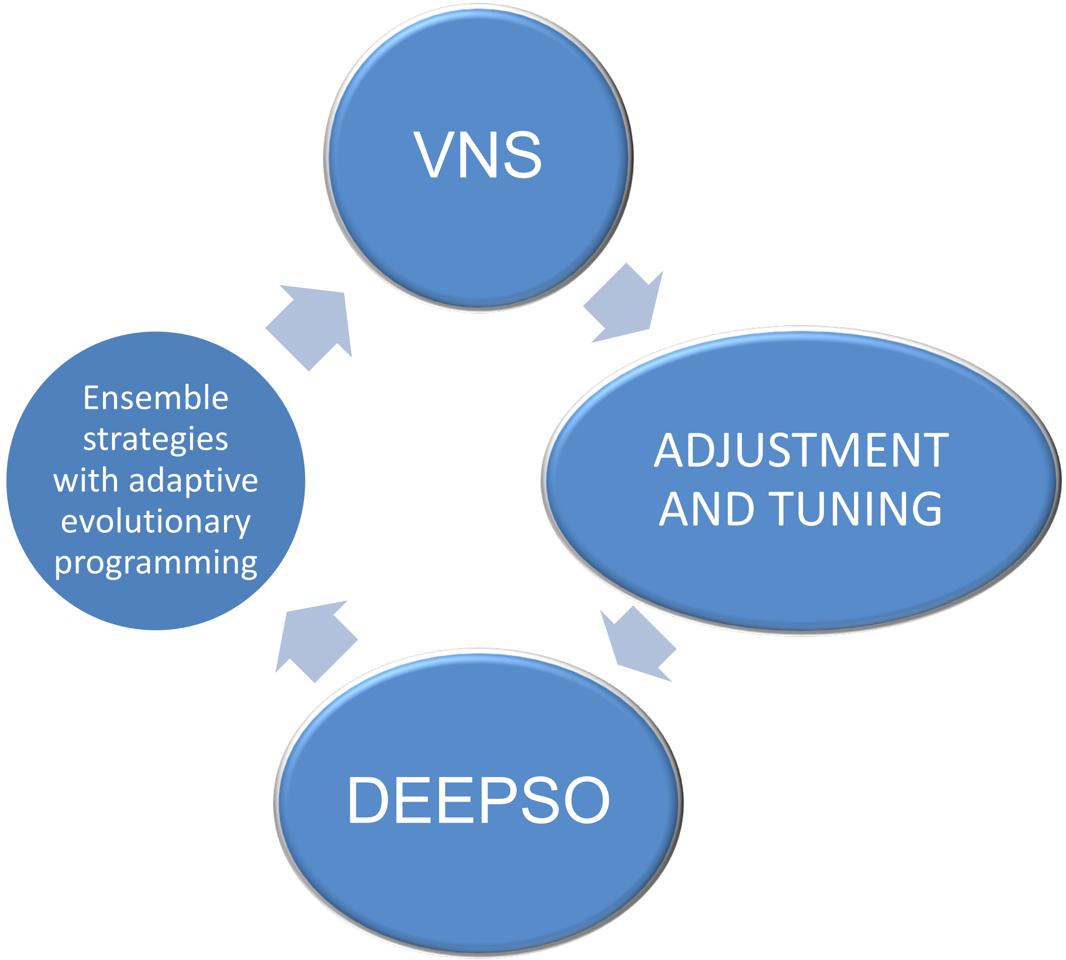
7. Combination VNS-DEEPSO



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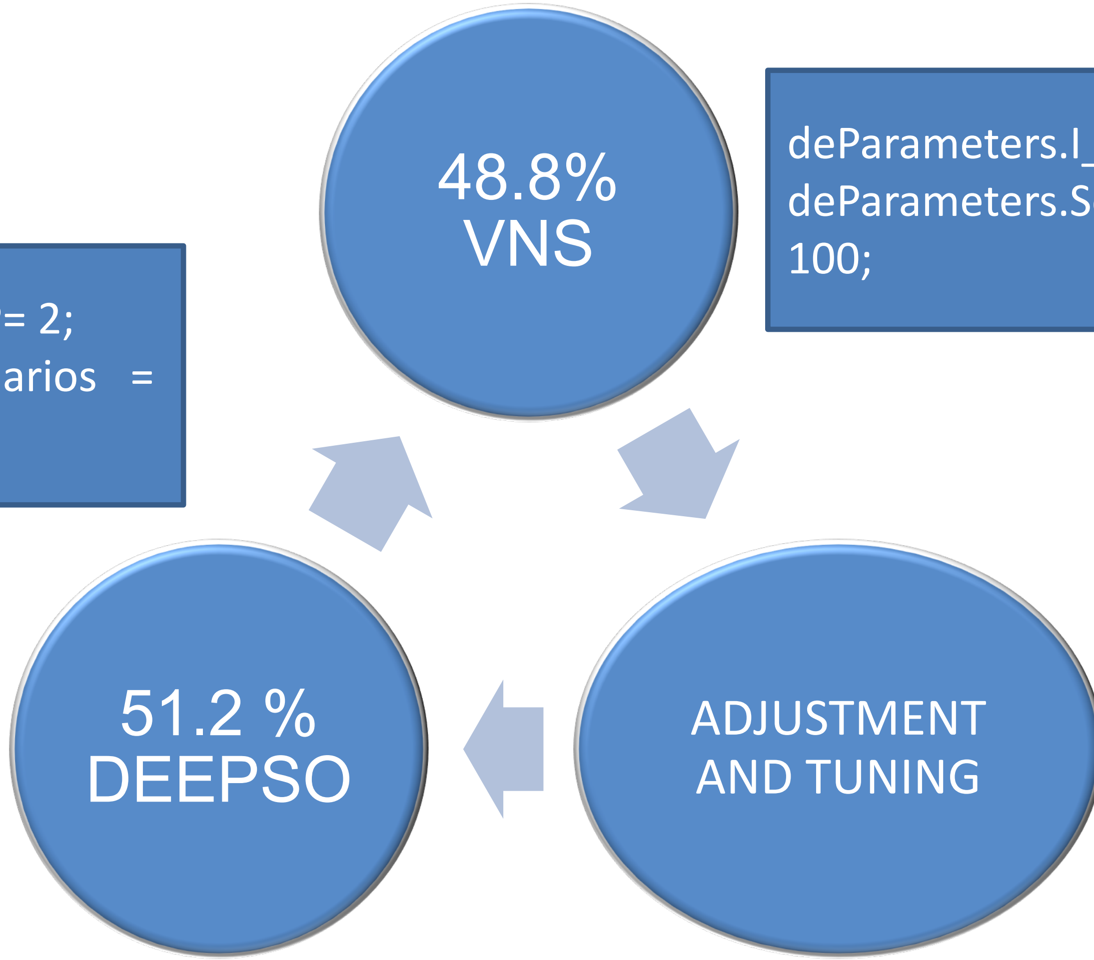
7. Combination VNS-DEEPSO

deParameters.I_NP= 1;
deParameters.Scenarios = 100;

deParameters.I_NP= 2;
deParameters.Scenarios = 100;



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8. Results

Runs	AvFit	StdFit	MinFit	MaxFit	varFit	Convergence Rate	Penalties
1	16,24	1,71	12,33	21,39	2,93	-0,00642807	0
2	16,48	1,82	12,60	21,48	3,30	-0,00251595	0
3	16,38	1,81	12,43	21,60	3,26	-0,00420768	0
4	16,41	1,84	12,41	21,61	3,37	-0,00359513	0
5	16,35	1,80	12,37	21,62	3,25	-0,00469033	0
6	16,47	1,80	12,66	21,42	3,25	-0,00269627	0
7	16,39	1,78	12,54	21,68	3,18	-0,00399138	0
8	16,54	1,81	12,16	21,79	3,28	-0,00163690	0
9	16,45	1,73	12,91	21,26	2,98	-0,00301557	0
10	16,44	1,86	12,44	21,76	3,47	-0,00319510	0
11	16,39	1,79	12,55	21,41	3,20	-0,00405867	0
12	16,37	1,70	12,33	21,10	2,87	-0,00432488	0
13	16,38	1,75	12,20	21,38	3,06	-0,00420897	0
14	16,48	1,83	12,31	21,85	3,36	-0,00251278	0
15	16,49	1,78	12,93	21,25	3,17	-0,00234803	0
16	16,35	1,83	12,34	22,18	3,36	-0,00432983	0
17	16,42	1,77	12,48	21,53	3,14	-0,00314872	0
18	16,37	1,76	12,79	21,38	3,11	-0,00424405	0
19	16,48	1,81	12,91	21,31	3,26	-0,00255836	0
20	16,47	1,83	12,56	21,98	3,36	-0,00274748	0

8. Results

RankingIndex	PAvgFit	PstdFit	PminFit	PmaxFit	PvarFit	validationCode
18,208	16,417	1,791	12,512	21,550	3,209	6D88+3322947.9036

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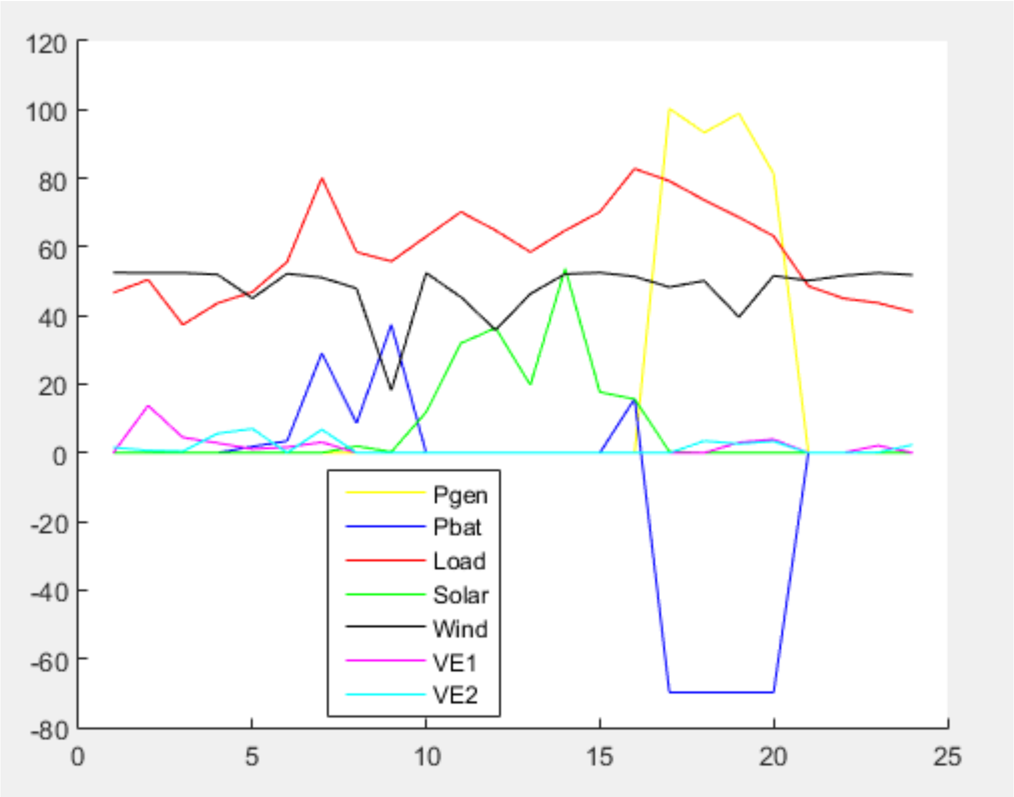
8. Current works

Optimal Operation of An Isolated Micro-Grid Considering Renewables Stochasticity, Battery Life and Dynamic PEV Charge Price



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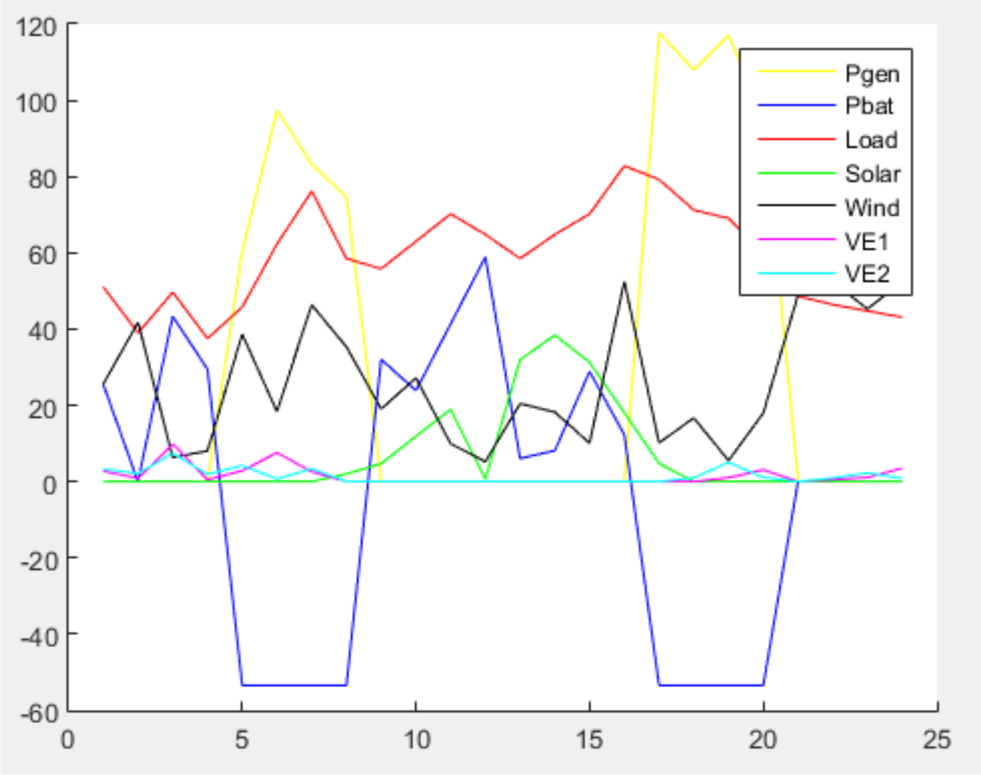

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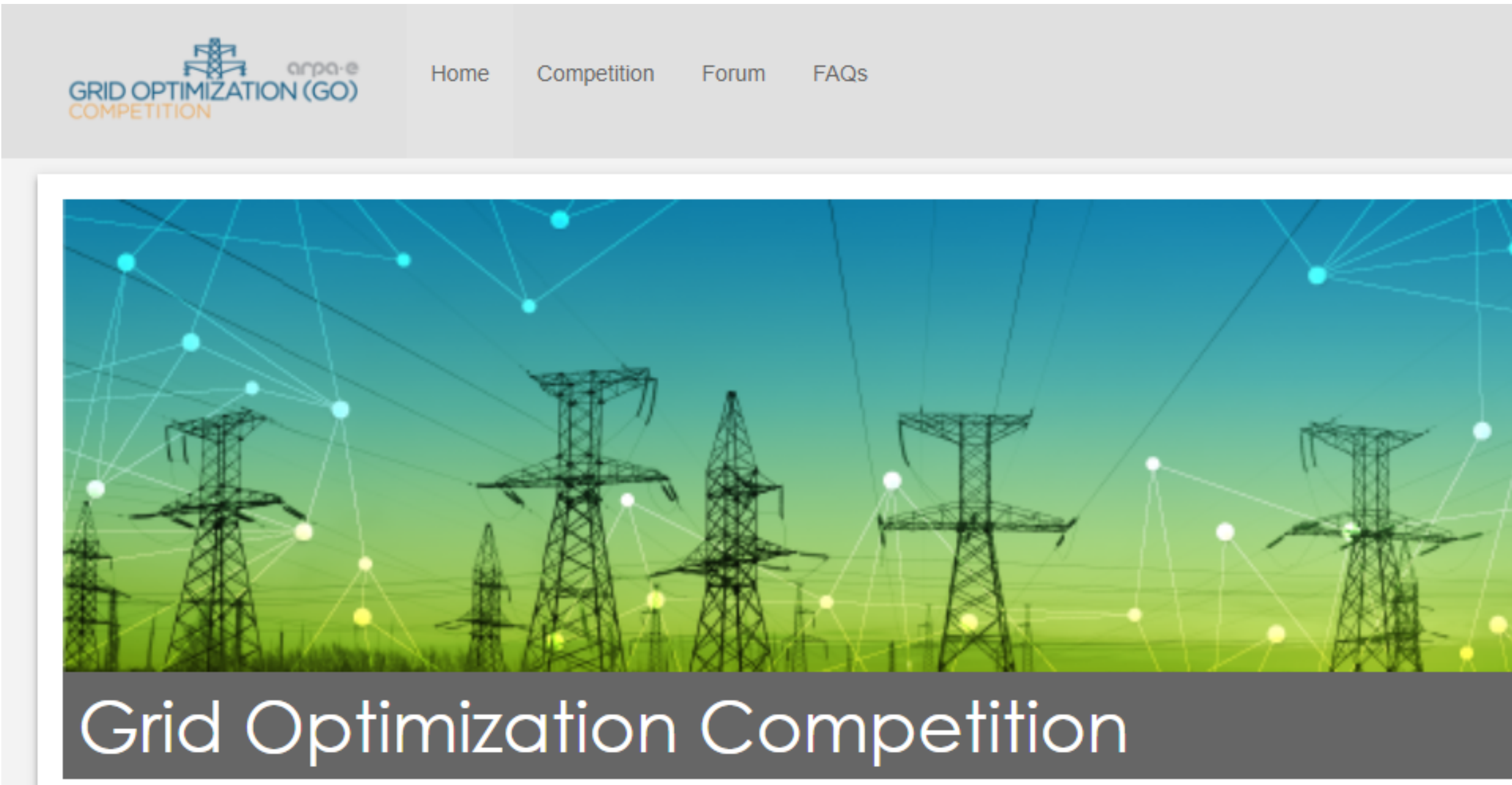

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