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# Optimized Frequency Control of Smart Grid Integrated with Electric vehicles using Ant Colony Optimization and Particle Swarm Optimization

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**Abstract:- Electric power generation at present reaches its greatest improvement with the help of renewable energy sources ,smart loads,electric vehicles.This paper deals with the power mismatches scenario with both primary and EV controller when EVs are connected to grid to achieve frequency control.Primary controller in power plant stabilizes frequency and EV controller deals with frequency deviation accordingly.PI controllers are used in both the scenarios and optimized with the help of Particle swarm optimization and Ant Colony optimization.**

## I. INTRODUCTION

Advantages of renewable energy sources over the conventional energy sources increasing gradually in this modern world.Electric vehicles plays a key role in achieving this scenario by providing great flexibility towards frequency controlling when connected to grid.several optimized techniques are applied to achieve good performance in its stability point of view.Particle swarm optimization and Ant colony optimization techniques are applied in such a way to optimize such scenario to study system to get desired performance.

## II. PROPOSED SYSTEM

Primary and Ev controller are equipped with proportional and integral controllers.Instability is caused by dynamic load and power generation in system.Optimal controller variable Kp and Ki is identified with the help of Particle swarm optimization and Ant colony optimization techniques.

## III. EV-INTEGRATED SMART GRID

Integrated electric vehicles in smart grid are analyzed with different loads connected to grid having renewable energy sources and a conventional governer-turbine system with smart homes. Notations represented as

$U_P$ ,$U_e$=primary ,EV control signals
$U_{e1}$, $U_{e2}$, and Uen = EV aggregators control signals. $\Delta P_{e1}$, $\Delta P_{e2}$, and $\Delta P_{en}$ = power output change of aggregators.

$\Delta f$ , $\Delta X_g$ = deviation of frequency, governor position change
$\Delta P_e$,$\Delta P_t$ = output power change of EV aggregators,turbine
$\Delta P_d$ ,$\Delta P_{re}$ = mismatch power of wind and load change.

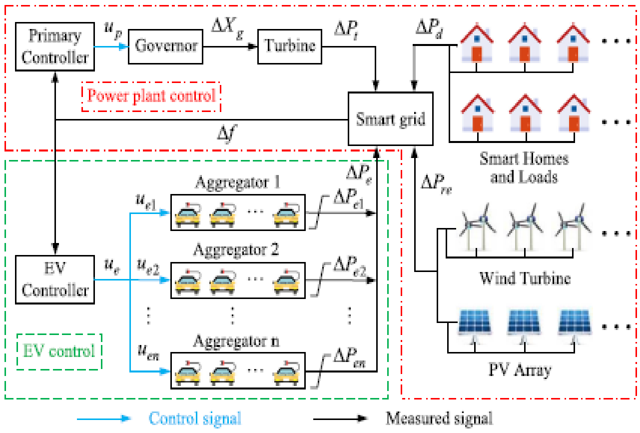


Fig1: EV integrated smart grid

This block diagram represents the electric vehicle integration with smart grid.

$T_t$ ,$T_g$, $T_p$ =turbine time constant, governor time constant, system time constant

Kp,R= power syatem gain ,speed regulation coefficient.
KA1, KA2, and KAn Variations of discharge and charge coefficients are small defined as for n EVs.
$\xi_1$, $\xi_2$ = primary, EV control distribution coefficients, $\xi_1 + \xi_2$ = 1.

$T_{e1}$, $T_{e2}$, $T_{en}$ =Time constants of EV's for the respective aggregators.

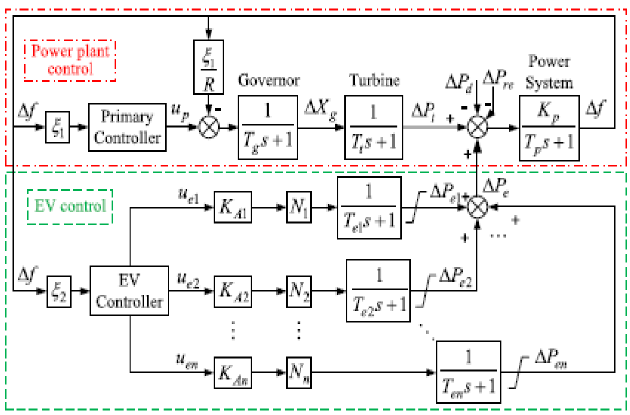


Fig2: smart grid control structure

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## IV. CONTROL MODEL USING PI

Block diagram of PI controller is as shown

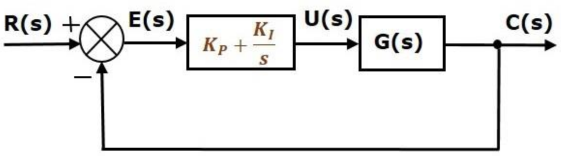


Fig3: PI controller closed loop system

There is reduction in steady state error and the same is observed with the help of simulation results.

## V. PSO AND ANT COLONY OPTIMIZATION

Particle swarm optimization is an optimization technique based on movement of swarms and its intelligence. Direct or indirect searching is possible to communicate with these particles.Particle swarm optimization algorithm helps in finding global optimum over a search space by set of particles.For every iteration particle positions gets updated and gels in finding global and local maximum accordingly.

Ant colony optimization is a population-based metaheuristic used to find solutions for optimization problems. A set of software agents called artificial ants search for good solutions to a given optimization problem. To apply ACO, the optimization problem is transformed into the problem of finding the best path on a weighted graph. Moving on the graph, artificial ants produce solutions for optimization problems.

## VI. SIMULATION AND RESULTS

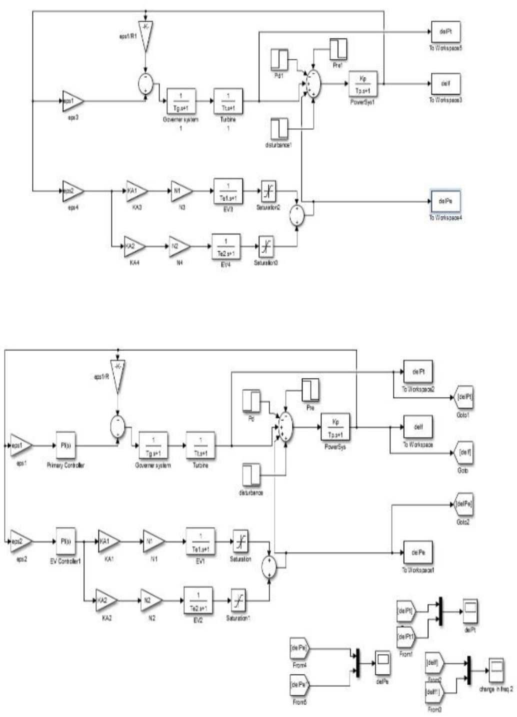

Fig4. Simulink Model for PI controller

Parameters: $T_t = 0.3$, $T_g = 0.1$, $T_p = 10$, $K_p = 1$, $R = 0.05$, $\xi_1 = 0.2$, $\xi_2 = 0.8$. $T_{e1} = T_{e2} = 0.035$, $K_{A1} = K_{A2} = 0.0024$ power constraints [-0.5,0.5]. $K_{PP} = 15$ , $K_{IP} = 40$ and $K_{PE} = 0.2$ and $K_{IE} = 2$ for EV control.

**PSO AND ACO PARAMETERS:**

| | |
|---|---|
| Max Iteration | 15 |
| Swarm Size | 10 |
| Inertia Weight(w) | 1 |
| Inertia Weight Damping Ratio(wdamp) | 0.999 |
| Personal Learning Coefficient($C_1$) | 1.5 |
| Global Learning Coefficient($C_2$) | 0.5 |

Table1: PSO parameters

| | |
|---|---|
| Max Iteration | 15 |
| Archive Size | 10 |
| Intensification Factor (Selection Pressure) | 0.5 |

Table 2: ACO parameters

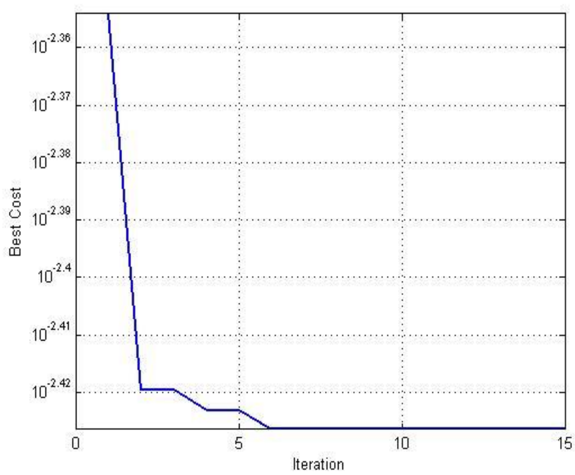


Fig5. Best cost vs iteration for PSO

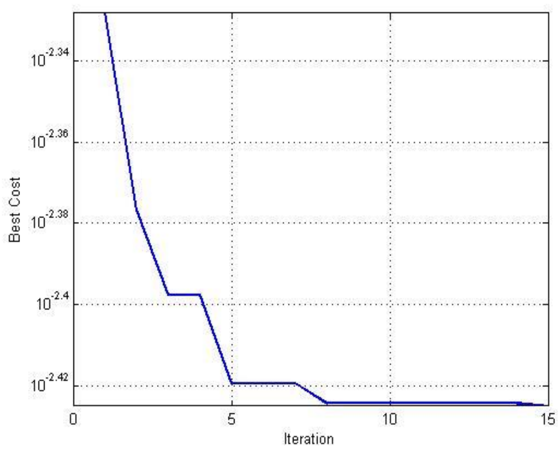


Fig 6 Best cost vs iteration for ACO

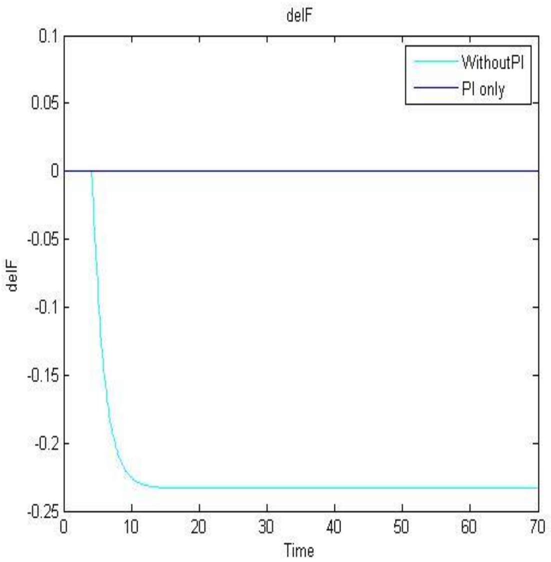


Fig 7 Time Vs $\Delta f$

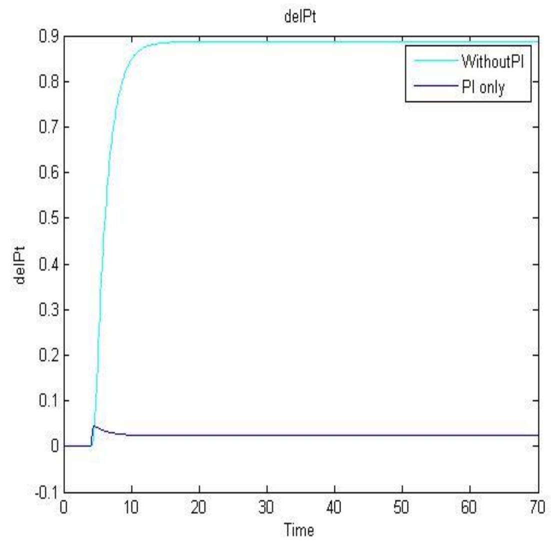


Fig 8 Time Vs $\Delta P_t$

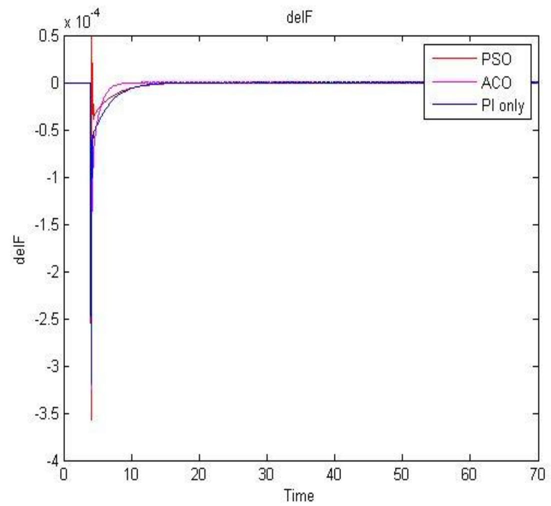


Fig 9 Time Vs $\Delta f$

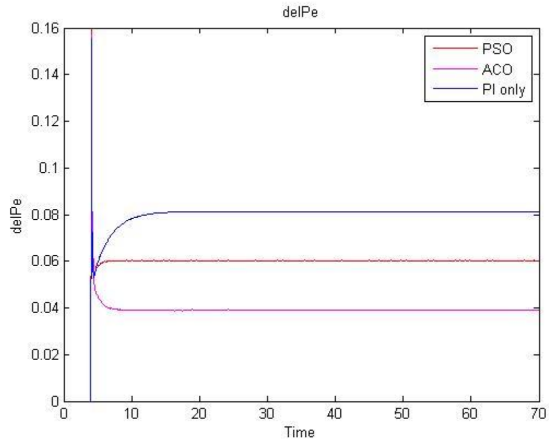


Fig 10 Time Vs $\Delta P_e$

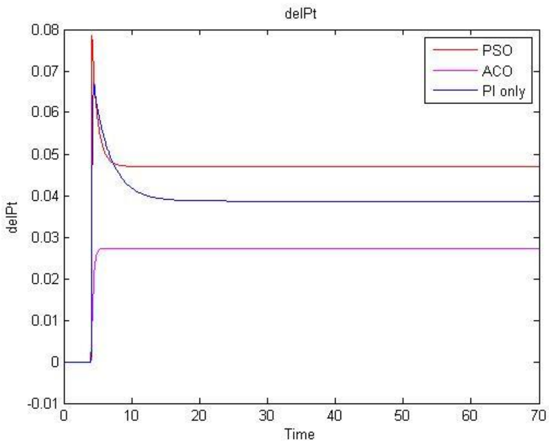


Fig11 Time Vs $\Delta$Pt

## VII. CONCLUSION AND FUTURE WORK

When ever power mismatches occur, both primary controller and EV controller participate in reducing the deviations of frequency.Instability due to dynamic load and power generation is reduced by obtaining proportional and integral gains Kp, Ki. System is restored by optimized frequency control of Ant colony optimization and Particle swarm optimization. In future other optimization techniques are also evolving and these are to be applied and compared the results and best optimized parameters are obtained for frequency control.

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