DYNAMIC LOAD SCHEDULING OPTIMIZATION OF POWER PLANTS

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Abstract - In this paper a Mixed Integer Dynamic Optimization (MIDO) framework is exploited for combined Unit Commitment and Economic Load Scheduling (UCELS) optimization of power plants. Economic load scheduling optimization problem is formulated as a Dynamic Optimization (DO) problem that allows us to optimize the plant operations by taking into account the time varying dynamics. Dynamic optimization problem together with the switching (on/off) states of the generating units as binary decision variables is formulated as MIDO problem. Load scheduling optimization of a power plant is carried out with the objective of minimizing a cost function that includes fuel cost, emission cost, start-up cost, shutdown cost, equipment ageing cost and penalty cost for not meeting load demand. Typical constraints for the optimization problem that are considered here include ramping constraints, minimum and maximum load constraints associated with the power plant units e.g., gas turbine, boilers, steam turbine, etc. MIDO problem thus formulated is solved using the dynamic optimization tool equipped with a Mixed Integer Linear Programming (MILP) solver. Models for the power plant units are developed using the object oriented modeling language, Modelica^{TM}. In this study, a typical Combined Cycle Power Plant (CCPP) and Fossil Fired Power Plant (FFPP) configuration is considered for the verification of load scheduling optimization solutions for different scenarios.

Keywords—Load scheduling; Power plant; MIDO; CCPP; FFPP

I. INTRODUCTION

Economic load scheduling (ELS) optimization means optimally distributing load between different heat and power generating units in a power plant. If the decision on switching states (on/off) of the generating units is also considered, then the problem becomes a combined Unit Commitment and Economic Load Scheduling (UCELS) optimization. Hence the UCELS optimization problem accommodates both the continuous states (e.g. heat/electrical/steam output) and integer states (e.g., on/off states of the boilers/turbines) as the decision variables.

A variety of optimization techniques has been applied in solving the economic load dispatch problem. References [1] explored the feasibility to solve the economic emission dispatch problem using classic optimization techniques such as linear or quadratic programming. Fuzzy based techniques to solve the combined emission and economic dispatch problem are reported in [2] and [3]. Reference [4] has used artificial intelligent techniques like neural network. Reference [5] has used genetic algorithm for solving the economic dispatch problem in power plants. The use of hybrid genetic algorithms in solving the emission and economic dispatch is reported in [6]. Reference [7] has considered the lifetime cost of the power units in the load scheduling optimization. Reference [8] has developed particle swarm optimization algorithm based technique for solving emission and economic dispatch problem. Reference [9] has used Newton-based algorithm, [10] has used Pattern Search method to solve various types of economic dispatch problem like economic dispatch with valve point (EDVP), multi-area economic load dispatch (MAED), combined economic environmental dispatch (CEED) and cubic cost function economic dispatch (QCFED).

Most of the work already done in the area of ELS optimization of power plants mainly consider fuel cost in the optimization criterion for optimal scheduling while meeting the power demand. A mixed integer linear programming (MILP) based unit commitment problem among power generation unit is addressed in [14] only based on fuel cost. Due to stricter environmental regulations, emissions cost should also be considered for ELS. Emission costs are the costs incurred in treatment of the emissions produced during the power generation. ELS with fuel cost and emission cost as the optimization objective has also been considered in the literature. Another important cost factor that is considered in the literature for ELS optimization is ageing cost [7]. Ageing cost of the power plant units is calculated based on the equipment life, operating conditions and their depreciation rate. In addition to these cost factors, the startup cost and the shutdown cost of the power plant units is also important in load scheduling optimization formulation.

In this paper, a formulation of UCELS optimization problem of Combined Cycle Power Plant (CCPP) is attempted. A representative CCPP prototype model is used to solve the UCELS optimization problem. This novel approach considers fuel costs, emission pollutant treatment cost, equipment start-up and shut-down costs and equipment aging cost to arrive at the optimal load scheduling solution. The major constraints for optimization are minimum and maximum load constraints, maximum number of start-ups /shut-downs and load ramping constraints of plant units.

A Mixed Integer Dynamic Optimization (MIDO) [11] framework is exploited in this work for solving UCELS problem in power plants. In the current work, UCELS problem is formulated as a dynamic optimization (DO) problem that allows us to optimize the load scheduling between generating units of power plant by taking into account their time varying dynamics. The UCELS optimization problem becomes MIDO problem since binary decision variables (On/Off state) are considered. The power plant unit models were developed using the Modelica^{TM} language that uses the object oriented modeling methodology. The Modelica^{TM} language tools used during the work, supports models represented by Ordinary Differential Equations (ODEs), Differential-Algebraic Equations (DAEs), bond graphs, finite state automata, Petri nets etc. [12]. The object orientated approach in Modelica^{TM} has brought modeling much closer to the way in which an engineer assembles individual units to build a complete system. Models developed using these approaches are generic and flexible in their usage. Such an approach reduces the efforts in the development of models and enhances their reusability so that the overall costs of development and maintenance of simulation models is reduced. Also Modelica^{TM} language tool enables symbolic representation of the equations that can be translated automatically to xml and c# files that can be interfaced with external optimization platforms.

The paper is organized as follows. In section II, a typical CCPP model configuration is explained. The optimization problem formulation and the cost models are described in section III. Load scheduling optimization results of CCPP model for different test cases are discussed in detail in section IV. In section V, a typical FFPP model configuration and preliminary load scheduling optimization results are presented. Conclusions are provided in section VI of this paper.

II. COMBINED CYCLE POWER PLANT MODEL

Fig. 1 shows a typical CCPP configuration , with combined power and district heating), is used in this study. The gas source (natural gas) is compressed and burnt in the combustion chamber of the gas turbine (GT) which, coupled with the electrical generator, produces the electrical energy. The heat available in the flue gas coming out from the GT is utilized to produce High Pressure (HP) and Low Presure (LP) steam in HRSG units. In addition, the HRSGs are provided with duct burners (natural gas is used as fuel) to heat the flue gas coming out from GTs. The HP and LP steam produced in HRSG is then sent to HP & LP steam headers respectively. From the steam headers, the steam (HP & LP) will be directed to the district heating applications (DH) to meet their heat demands and also to steam turbine (ST) for power generation.

The GT and HRSG units are modeled using the piecewise linear approximation of their non-linear input-output characteristics data using two point convex/concave method. These linear models are then used to develop the CCPP model for solving load scheduling optimization problem. The main objective of this problem is to meet the load (power and / or heat) demand by scheduling the load among the multiple generation units, subjected to the minimization of the fuel cost, startup cost, shutdown cost, emission cost and equipment ageing costs.

Emission cost models for each pollutant (NOx, COx, SOx) are designed using the piecewise linearization of the non-linear functions [13]. Lifetime cost models are designed considering the effect of electrical load on each unit. These models are explained in detailed in section III.

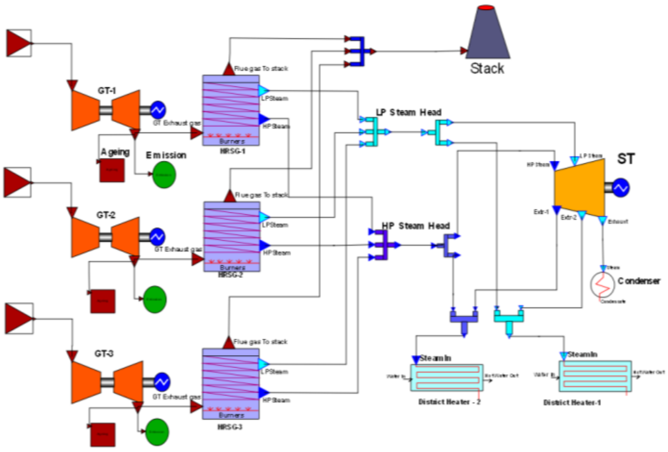

Fig. 1: Combined Cycle Power Plant Model developed using the Modelica^{TM}

III. PROBLEM FORMULATION

The problem formulation (objective function and constraints) for the CCPP configuration as shown in *Fig. 1* is explained further in this section.

A. Objective Function

The UCELS optimization problem is solved using Mixed Integer Linear Programming (MILP) technique with the objective of minimization of the cost function *J*.

where, $$\min_{u_1,u_2,u_3,u_4,u_5,u_{l1},u_{l2},u_{l3}} J$$

$$J = C_{dem} + C_{fuel} + C_{start,shut} + C_{emission} + C_{ageing} - C_{revenue} \quad (1)$$

The decision variables u_1, u_2 and u_3 represent the electrical load of the respective GTs and the variables u_{l1}, u_{l2} and u_{l3} are binary variables which define the state of the GTs whether it is "on" or "off". u_4 and u_5 are the steam flow from HP and LP headers to the respective district heating applications to meet the heat demand.

Each of the terms in the cost function (J) is explained below.

C_{dem} is the penalty function for not meeting the electric demands over the prediction horizon:

$$C_{dem} = \sum_{t=0}^{M-1} k_{dem\ \mathrm{Elec}} \left| \sum_{i=1}^{n} y_{i2}(t) - D_{dem\ \mathrm{Elec}}(t) \right| + k_{dem\ \mathrm{Heat}} \left| \sum_{i=1}^{n} y_{i3}(t) - D_{dem\ \mathrm{Heat}}(t) \right|$$

(2)

For CCPP, the penalty function C_{dem} includes cost factors for not meeting both the electric and heat demands over the prediction horizon.

Where

$y_{i2}(t)$ is the actual power generated by the i^th^ unit,

$y_{i3}(t)$ is the actual heat produced by i^th^ unit

$k_{dem\ \mathrm{Elec}}$ and $k_{dem\ \mathrm{Heat}}$ are the suitable weight coefficients,

$D_{dem\ \mathrm{Elec}}(t)$ and $D_{dem\ \mathrm{Heat}}(t)$, for $t = 0,\ldots,(M-1)$ are the forecasts of the electrical and heat demand, respectively,

n is the number of generating units,

M is the prediction horizon.

C_{fuel} is the total cost of fuel consumption in all the generating units,

$$C_{fuel} = \sum_{t=0}^{M-1} \sum_{i=1}^{n} k_{i\ fuel}\, y_{i1}(t) \tag{3}$$

Where

$y_{i1}(t)$ is the fuel consumption in the i^th^ unit,

$k_{i\ fuel}$ is the cost of fuel consumption y_{i1}.

$C_{emission}$ is the cost involved in treating the pollutant emission (NO_x, SO_x, CO_x) produced by the power plant and is given by,

$$C_{emission} = \sum_{t=0}^{M-1} \sum_{i=1}^{n} k_{i\ emission} f\left(y_{i2}(t)\right) \tag{4}$$

where $k_{i\ emission}$ is the cost coefficient for emission treatment and $f\left(y_{i2}(t)\right)$ represents a linear functional relationship between the electrical load and the emission production as given by the following equation.

$$f(y_{i2}) = \alpha_i + \beta_i y_{i2} \tag{5}$$

α_i and β_i are emission constants.

$C_{start,shut}$ is the cost of starting/shutting of the turbines (GT & ST) and is given by,

$$C_{start,shut} = \sum_{t=0}^{M-1} \sum_{i=1}^{n} k_{i,start/shut} \left| u_{li}(t+1) - u_{li}(t) \right| \tag{6}$$

where $k_{i,start/shut}$ represent the shut down or start up cost for the i^th^ unit. u_{li}(t) and u_{li}(t+1) are the integer states (On/Off) of the i^th^ unit at the current and next sampling instance respectively.

C_{ageing} describes the equipment ageing cost and is defined as,

$$C_{ageing} = \sum_{t=0}^{M-1} \sum_{i=1}^{n} k_{i,ageing} \left(\frac{y_{i2}(t)}{y_{i2}^{base}} \right) \tag{7}$$

where,

$k_{i,ageing}$ is the cost coefficient of ageing for i^th^ unit and y_{i2}^{base} is the base load for the i^th^ unit which is assumed to be constant. The coefficient of ageing, $k_{i,ageing}$, may be function of load so as to appropriately penalize the operation at higher and lower than base loads. Therefore, if a unit is operated at base load, the ageing cost is $k_{i,ageing}$. In case, the unit is operated at double the base load, the ageing cost is $2k_{i,ageing}$.

The term $C_{revenue}$ is the revenue earned from both the electric power and heat sales. Thus $C_{revenue}$ term is described as follows,

$$C_{revenue} = \sum_{t=0}^{M-1} \sum_{i=1}^{n} p_{i,\mathrm{Elec}}(t) y_{i2}(t) + p_{i,\mathrm{Heat}}(t) y_{i3}(t) \tag{8}$$

where, $p_{i,Elec}(t)$, $p_{i,\mathrm{Heat}}(t)$ are the cost coefficients for the sale of electric power and heat respectively.

B. Constraints

The above described optimization problem in equation (1) is subjected to one or more of the following constraints:

a) Minimum & Maximum load constraints for gas turbines coupled with generators

$$u_{i,\min} \le u_i \le u_{i,\max} \tag{9}$$

b) Ramp up and ramp down constraints for gas turbines:

$$\frac{d(u_i)}{dt} \le ramp_{\max} \tag{10}$$

$$\frac{d(u_i)}{dt} \geq ramp_{\min} \tag{11}$$

c) Constraint on maximum number of start-ups and shut-downs for gas turbines.

IV. RESULTS AND DISCUSSION

In this section, three different test cases are considered to verify the load scheduling optimization results for the CCPP model. The load scheduling optimization problem was formulated as a MILP and solved using the dynamic optimization framework with LPSolve as MIP solver. Optimal load scheduling results presented in this section are corresponding to 1-day ahead scheduling with 1 hr sampling interval. Load scheduling optimization results obtained for the three different case studies are discussed in the following sub sections. The electric power and heat demand profiles considered in the case studies are depicted in *Fig. 2* and *Fig. 3* respectively. These figures also show that actual power and heat generated by generating units match exactly with the respective demands for all the 3 case studies discussed below.

A. *Case-1:Effect of fuel cost in scheduling*

The effect of fuel cost in load scheduling optimization for a varying power and heat demand profiles as shown in *Fig. 2* and *Fig. 3* are described in this section. In this case study, GTs are considered with different fuel costs ($k_{1\,fuel} < k_{2\,fuel} < k_{3\,fuel}$). i.e., GT-1 has the lower fuel cost than GT-2 and GT-2 has lower fuel cost than GT-3.

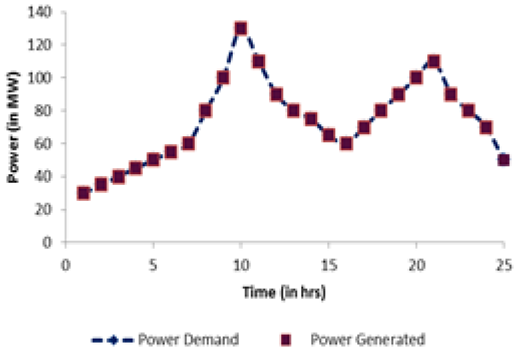

Fig. 2: Power demand and generation profiles

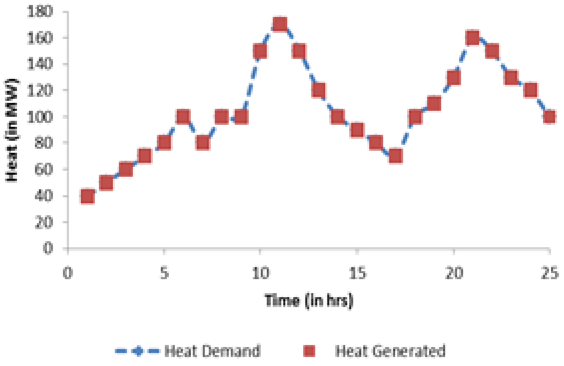

Fig. 3: Heat demand and generation profiles

Optimal load scheduling results for gas turbines (GT-1, 2, 3) are shown in *Fig. 4*. It has been observed from *Fig. 4* that GT-1 contributes the highest in meeting the power demand in comparison to GT-2 and GT-3 because GT-1 has the lowest fuel cost. Similarly, GT-2 contributes more in meeting the power demand than GT-3. The flue gas output from the corresponding gas turbines are then passed to Heat recovery steam generators for steam generation to meet the heat demand profile (*Fig. 3*) for district heaters (DH-1 & DH-2) as shown in *Fig. 1*. In addition to power generation by all the gas turbines, the steam turbine utilizes the steam generated by HRSGs for the power generation to meet the power demand. Power generated by the steam turbine is shown in *Fig. 4*. In the optimization problem, the constraints on the maximum number of startups and shutdowns for the gas turbine units (maximum Startups and Shutdowns = 2) are considered for the prediction horizon of 24 hrs. From the load scheduling results in *Fig. 4*, it is evident that the optimizer satisfies these constraints. Consider the GT-3 load scheduling profile in *Fig. 4*. As GT-3 has the highest fuel cost, it can be switched off from time 22 to 25 hrs, where GT-1 and GT-2 have sufficient reserve power generation capacity to take care of power demand. Instead, GT-3 has been allocated with minimum load from time 22 hrs to 25 hrs in order to satisfy the constraint of maximum number of shutdowns.

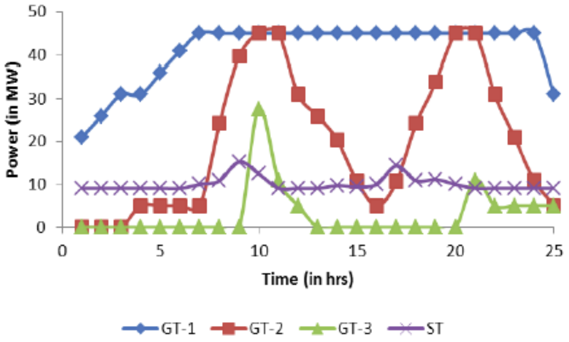

Fig. 4: Optimal power generation scheduling for GTs & ST for Case-1

B. *Case-2: Effect of fuel & emission cost in scheduling*

In addition to the fuel cost of GTs, the emission treatment costs are also included into the overall objective function. In this case study, gas turbines 1, 2 and 3 are considered with increasing order of fuel costs, similar to that in case-1 ($k_{1\,fuel} < k_{2\,fuel} < k_{3\,fuel}$). Emission treatment costs for the gas turbines are considered in the order, $k_{3\,emission} > k_{1\,emision} > k_{2\,emission}$. It can be observed that GT-3 has the highest fuel and emission cost in comparison with GT-1 and GT-2. On the other hand, GT-1 has lower fuel cost than GT-2 but higher emission treatment cost than GT-3. The results of optimal load scheduling for gas turbines (GT-1, 2 and 3) and the steam turbine power generation in meeting the varying power demand is shown in *Fig. 5*. The values of the coefficients are chosen such that emission cost factor is larger than the fuel cost. Hence, it is expected that

GT-2 should contribute highest in power generation and the same has been observed from the results in *Fig. 5*. Since GT-3 has the highest fuel and emission handling costs it is taking the least part in meeting the power and heat demands. Further, at the maximum power demand point, i.e. at time instants10 and 21 hours, both GT-1 and GT-2 are operated at their maximum generation limit of 45 MW and the rest of the power demand is met by ST and GT-3.

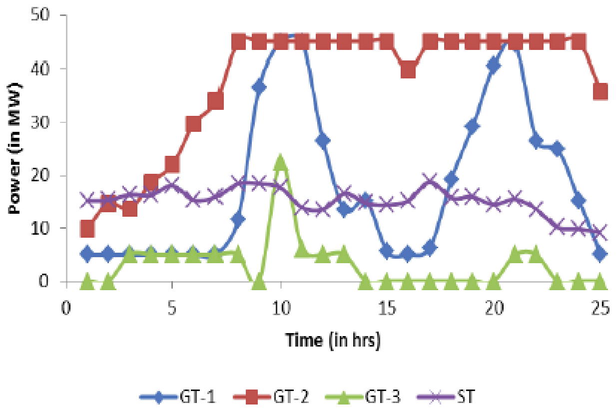

Fig. 5: Optimal power generation scheduling for GTs & ST for Case-2

C. *Case-3: Effect of fue, emission and ageing cost in scheduling*

In addition to the fuel and emission costs mentioned in case-2, the ageing cost for gas turbines is also considered in the overall objective function of the optimization to verify the effect of ageing in load scheduling. In this case study, the following cost (fuel/emission/ageing) variation orders are considered:

Fuel Cost: $k_{1\,fuel} < k_{2\,fuel} < k_{3\,fuel}$,

Emission Cost: $k_{1\,emission} > k_{3\,emision} > k_{2\,emission}$,

Ageing Cost $k_{1\,ageing} > k_{2\,ageing} > k_{3\,ageing}$.

Among three gas turbines, GT-1 is assumed to have the highest emission treatment and ageing costs with respect to GT-2 and GT-3. Hence, it is expected that GT-1 should contribute the least to meet the power demand as depicted in *Fig. 6*. It can be observed from *Fig. 6* that at the maximum power demand point, i.e., at time instant 10 and 21 hours, both GT-2 and GT-3 are operated at their maximum production limit of 45 MW and the rest of the power demand is met by ST and GT-1 as expected based on the relative values of the cost coefficients.

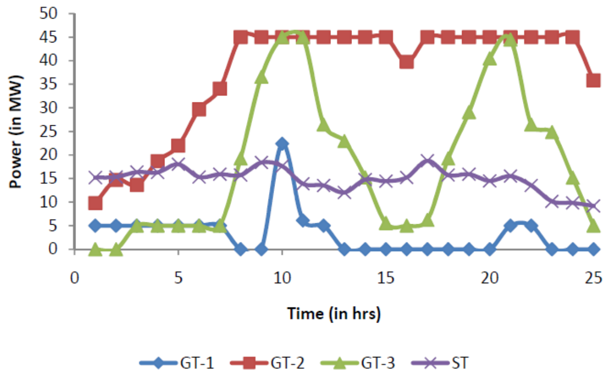

Fig. 6: Optimal power generation scheduling for GTs & ST for Case-3

V. FOSSIL FIRED POWER PLANT MODEL

Fig. 7 shows a typical FFPP configuration used in this study. Six high pressure (HP) boilers are used to generate HP steam and fed into the HP header. There are four steam turbines (ST1- ST4) with extractions are utilizing the steam from HP header for electric power generation to meet the overall power demand. There are three pressure reducing valves (PRVs) placed between different headers (PRV1 is between HP to intermediate pressure (IP) header, PRV2 is between HP to low pressure (LP) header, PRV3 is between LP to LP-2 header). There exist three steam stations (HPS, IPS & LPS) has their corresponding steam demands (HP, IP, LP). Steam to the steam stations are supplied by the corresponding steam headers as shown in the figure. Further, there are two low pressure (LP) boilers generating LP steam and fed to LP-2 header. Load scheduling optimization is performed for FFPP model and optimal values of load scheduling for boilers' steam generation set points, PRV steam flows, Steam turbines' extractions and makeup water supply in order to meet the overall power and steam (HP, IP & LP) demand profiles over a scheduling period of 12 hour with a sample interval of 1 hour is obtained. For this particular problem, only fuel cost of boiler is considered which has different fuel consumption characteristics obtained based on the plant data.

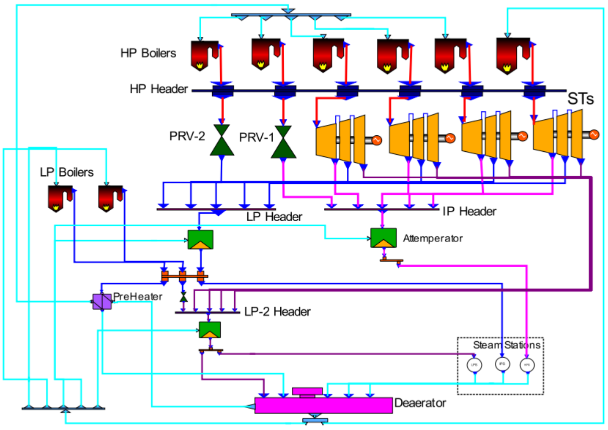

Fig. 7: Fossil Fired Power Plant Model developed using the Modelica^{TM}.

The power, HP steam and LP steam demand and expected profiles for the FFPP model are shown in *Fig. 8*, *Fig. 9,* respectively. *Fig. 10* shows the distribution of steam production between different boilers.

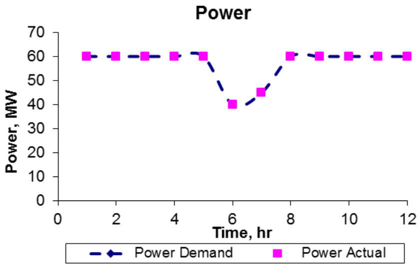

Fig. 8: FFPP Model Power Profile

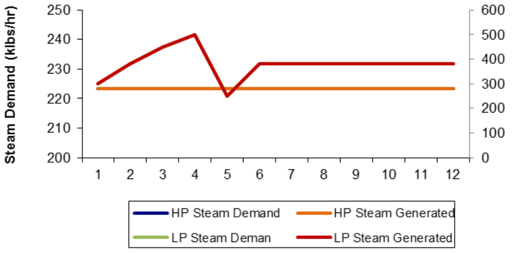

Fig. 9: FFPP Steam Demand Profile

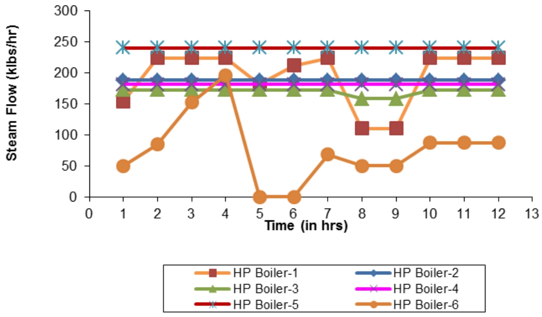

Fig. 10: FFPP LP Steam Demand

VI. CONCLUSIONS

In the current work, combined unit commitment and economic load dispatch problem is addressed using MIDO framework for CCPP and FFPP model configuration. The optimization formulation in this work considers equipment ageing cost and startup/shutdown cost also along with traditional fuel and emission costs for optimal load scheduling. A generalized approach to formulate the ageing cost is presented which can be customized and easily extended to specific requirements. For instance, one can also penalize the ageing effect due to frequent changes in load by appropriately including it as ageing cost of the equipment. Different case studies are presented to verify the results of load scheduling using MIDO based approach. Various constraints such as maximum number of start-ups and shut-downs for the generating units are also considered and the effect of the same has also been verified in the case studies.

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