

UNIFIED PROPORTIONAL INTEGRAL DERIVATIVE LOAD FREQUENCY CONTROL VIA PARTICLE SWARM AND HYBRID PARTICLE SWARM MODEL PREDICTIVE OPTIMIZATION FOR HYDRO THERMAL POWER SYSTEMS

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ABSTRACT

Frequency regulation in hydro–thermal systems is complicated by the slow reheat dynamics of steam units and the non-minimum-phase response of hydro penstocks. This paper develops a unified proportional–integral–derivative (PID) load frequency control (LFC) scheme, in which a single set of secondary gains serves both control areas, and tunes it with standard particle swarm optimization (PSO) and with a hybrid PSO–model predictive control (PSO–MPC) framework. The test system is a 1500 MW two-area network: Area 1 holds two 500 MW reheat tandem-compound steam units and Area 2 a single 500 MW hydro unit, linked by a tie-line. Instead of textbook defaults, the steam-chest, reheater and crossover time constants (0.36 s, 5.09 s and 0.40 s) and the turbine stage power fractions (0.273, 0.351 and 0.376) were derived from the heat balance diagram of a 500 MW unit and interpolated superheated-steam tables. The PSO objective was the integral of time-weighted absolute frequency error (ITAE) summed over both areas. Responses to 1.0 Pu. step load disturbances were simulated in MATLAB/Simulink R2023b and compared with a Ziegler–Nichols (Z-N) baseline. The Z-N controller kept the system stable but left a persistent frequency offset of 0.005–0.009 Hz, whereas both optimized controllers returned the frequency to 50 Hz. The hybrid PSO–MPC scheme reached an ITAE cost of 297.99 against 422.18 for standard PSO, a 29.4% reduction, with the smallest Area 1 undershoot, although its transient advantage over PSO was small. A single coordinated gain set therefore suffices for a mixed hydro–thermal system, without area-specific tuning.

Keywords: Load frequency control; hydro–thermal power system; particle swarm optimization; model predictive control; unified PID controller; heat balance diagram.

1 INTRODUCTION

An interconnected power grid stays at its nominal frequency only while generation matches a load that never stops moving [1, 2]. Any mismatch between the two appears first as a frequency deviation from 50 Hz. Left uncorrected, sustained deviations stress turbine blades, push transformer cores toward saturation and, in the worst case, trigger load shedding or loss of synchronism [1, 2]. In a multi-area network the problem is not contained locally, because a load change in one area is felt immediately in its neighbours through the tie-lines [2, 3]. Load frequency control (LFC) is the secondary regulation layer that removes the residual frequency error left by the governors and returns tie-line interchange to its scheduled value [1, 3]. Hydro–thermal systems are common because thermal

units carry base load cheaply while hydro units supply fast reserve [1, 3]. The pairing is awkward from a control standpoint. A reheat tandem-compound steam turbine responds through a chain of lags associated with the steam chest, the reheater and the crossover piping, and the reheater lag alone can reach several seconds [1, 4]. A hydro turbine behaves in the opposite way at first: when the wicket gates open, water inertia in the penstock causes the mechanical power to dip before it rises, a non-minimum-phase effect characterized by the water starting time T_w [5, 6]. A secondary controller in such a system has to cope with one area that is sluggish and another that initially moves the wrong way. PID controllers remain the industrial default for LFC because they are simple and cheap to implement [2, 7], but their performance depends almost entirely on the three gains K_p , K_i and K_d . Empirical rules such as Ziegler–Nichols (Z-N) assume a linearised plant and tend to give large overshoots, long settling and, in practice, residual offsets in multi-area hydro–thermal models [7, 8]. Metaheuristic tuning, and PSO in particular, has therefore become popular [9, 8, 11]. Two difficulties persist in much of that work. Controllers are usually tuned independently for each area, doubling the number of decision variables and allowing the two areas’ controllers to work against each other through the tie-line [2, 3]. And thermal turbine parameters are typically taken from generic textbook values rather than derived from a physical plant [4, 12]. This paper addresses both points. Its contributions are: (i) a two-area hydro–thermal model whose steam-turbine time constants and power fractions are derived from the heat balance diagram (HBD) of a 500 MW unit and superheated-steam tables; (ii) a unified PID secondary controller in which one gain set (K_p, K_i, K_d) acts in both areas, reducing the tuning problem to three dimensions; and (iii) a comparison of Z-N, standard PSO and hybrid PSO–MPC tuning of that controller under 1.0 Pu. step load disturbances.

2 RETERATURE REVIEW

Evolutionary algorithms were among the first metaheuristics applied to LFC. Genetic algorithms encode controller gains as chromosomes and evolve them against an integral error index; they improve on classical tuning but converge slowly and are sensitive to population size and mutation rate [13, 14]. Differential evolution explores the search space more efficiently through difference-vector mutation, yet its behavior hinges on the mutation factor and crossover rate, and many iterations are often needed on nonlinear models [15, 16]. Bacterial foraging and artificial bee colony methods have also been tried, with similar trade-offs between solution quality and computation time [13, 17, 18]. PSO has been favored because its update rules are simple and it usually converges quickly [9, 10]. Its known weakness is premature convergence to local optima, which several variants attempt to fix. Improved inertia-weight schemes widen the global search [19]; modified variants such as craziness-based PSO preserve swarm diversity at the cost of extra algorithmic complexity [10]; and adaptive PSO adjusts its coefficients during the run to improve disturbance rejection, which in turn raises computational demand [20]. Extending the controller itself is another route. Fractional-order PID controllers add flexibility but also two further parameters to optimize [21], while fuzzy-PID structures tuned by hybrid DE–PSO, teaching–learning or firefly–pattern-search algorithms improve damping at the expense of a more complicated controller [22, 23, 24]. Hybrid optimizers such as firefly–pattern search and multi-objective formulations strengthen global search but add parameters and run time [11, 14, 25]. Surveys of LFC in systems with distributed and renewable generation report that optimized PID controllers remain effective, although uncertainty in renewable output affects robustness [2]. Model predictive control approaches the problem differently: it uses an internal model to predict the system output over a horizon and computes control moves that respect generation-rate and valve limits [3, 26]. Standalone MPC performs well but solves an optimization problem at every sampling instant. Combining a metaheuristically tuned PID loop with a predictive element is a way of keeping the PID’s simplicity while borrowing some of the MPC’s anticipation [26]. Across this literature, most schemes either increase computational complexity or rely on separately tuned controllers in each area, and few derive thermal-turbine parameters from plant data. The work reported here targets that combination of gaps.

3 SYSTEM MODELLING

3.1 Thermal area

Area 1 consists of two identical 500 MW units, each driven by a reheat tandem-compound steam turbine with high-, intermediate- and low-pressure (HP, IP, LP) stages. Figure 1 shows the turbine

model. Steam passes the governor valve into the steam chest (time constant T_{SC}), expands through the HP stage, is reheated (T_{RH}), expands through the IP stage and reaches the LP stage via the crossover piping (T_{CO}). The fractions F_{HP} , F_{IP} and F_{LP} give each stage's share of shaft power, with $F_{HP} + F_{IP} + F_{LP} = 1$.

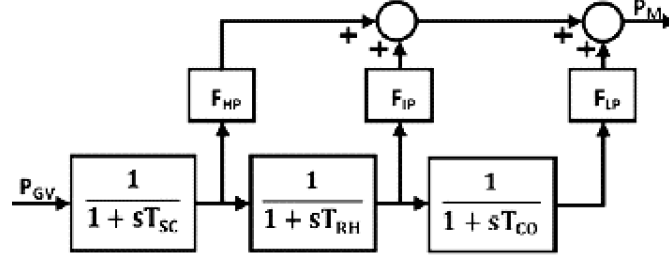


Figure 1. Dynamic model of the reheat tandem-compound steam turbine [4], [27]

Block-diagram reduction of Figure 1 gives the transfer function from governor output P_{GV} to mechanical power P_M [1, 4]:

$$G_t(s) = \frac{(F_{HP}T_{CO}T_{RH})s^2 + (F_{HP}T_{CO} + F_{IP}T_{CO} + F_{HP}T_{RH})s + 1}{(T_{CO}T_{RH}T_{SC})s^3 + (T_{CO}T_{RH} + T_{CO}T_{SC} + T_{RH}T_{SC})s^2 + (T_{CO} + T_{RH} + T_{SC})s + 1} \quad (1)$$

With the parameters derived in Section 3.2, this becomes.

$$G_t(s) = \frac{0.556s^2 + 1.639s + 1}{0.733s^3 + 4.012s^2 + 5.850s + 1} \quad (2)$$

The mechanical governor is represented by $1/(1 + sT_g)$ with $T_g = 0.25$ s [1], [27]. The two generators are lumped into one equivalent machine. Linearizing the swing equation with load damping D gives [1].

$$\frac{\Delta\omega(s)}{\Delta P_m(s) - \Delta P_L(s)} = \frac{1}{2H_{eq}s + D} = \frac{K_P}{1 + sT_P}, K_P = \frac{1}{D}, T_P = \frac{2H_{eq}}{D} \quad (3)$$

where the equivalent inertia of n machines of rating S_k is [28].

$$H_{eq} = \frac{\sum_k H_k S_k}{\sum_k S_k} \quad (4)$$

With $H = 5$ s for each unit and $D = 1$ Pu, $H_{eq} = 5$ s, $K_P = 1$ and $T_P = 10$ s. Each governor has a droop of 2.4 Hz/Pu. on its own base, i.e. 7.2 Hz/Pu. on the 1500 MW system base, so the three units in parallel give [1].

$$R_{eq} = \left(\frac{1}{R_1} + \frac{1}{R_2} + \frac{1}{R_3} \right)^{-1} = 2.4 \text{ Hz/p.u.} \quad (5)$$

3.2 Derivation of thermal parameters from the heat balance diagram

Each steam vessel was treated as a storage volume whose time constant depends on its size, the steam flow through it and how steam density changes with pressure at the operating temperature [4], [12]:

$$T = \frac{PV}{Q} \left(\frac{1/v_2 - 1/v_1}{p_2 - p_1} \right) \quad (6)$$

Here P (kPa) is the vessel pressure, V (m³) its volume, Q (kg/s) the mass flow, and v_1 , v_2 the specific volumes at bracketing pressures p_1 and p_2 . Pressure, temperature and flow at each point were read from the HBD of a 500 MW unit [4]; the HBD gives flow in t/h, pressure in kgf/cm² and enthalpy in kcal/kg, which were converted to SI units (1 kgf/cm² = 98.0665 kPa). Because the operating temperatures do not coincide with tabulated values, specific volumes were obtained from superheated-steam tables [29] by spline interpolation in MATLAB (*interp1*). The reheater volume was taken as two rows of tubes of average length 8 m, height 12 m and radius 0.4786 m; the steam chest as a cylinder 1.5 m high and 1.344 m in diameter; and the crossover as a pipe 8.5 m long and 2.60 m in diameter. Table 1 summarizes the calculation.

Table 1. Derivation of thermal time constants from HBD and steam-table data

Quantity	Steam chest	Reheater	Crossover
Vessel volume, V (m ³)	2.128	144.34	45.13
Mass flow, Q (kg/s)	404.72	361.47	301.88
Pressure, P (kPa)	16 671	3 971.7	699.2
Steam temperature (°C)	537.0	451.0	309.9
Bracketing pressures, p_1 / p_2 (kPa)	15 000 / 20 000	3 000 / 4 000	600 / 800
Specific volumes, v_1 / v_2 (m ³ /kg)	0.0224 / 0.0153	0.1080 / 0.0802	0.4424 / 0.3302
Time constant (s)	$T_{SC} = 0.36$	$T_{RH} = 5.09$	$T_{CO} = 0.40$

The reheater temperature is the mean of the cold-reheat (337.0 °C) and hot-reheat (565.0 °C) values. The reheater dominates, as expected; its 5.09 s lies within the 4–11 s range usually reported for utility-scale units [1, 4]. The power fractions follow from the stage outputs [4, 12]:

$$F_{HP} = \frac{1}{1+a_1+a_2}, F_{IP} = \frac{a_2}{1+a_1+a_2}, F_{LP} = \frac{a_1}{1+a_1+a_2} \quad (7)$$

with $a_1 = P_{LP}/P_{HP}$ and $a_2 = P_{IP}/P_{HP}$. Each stage output was computed from the HBD flows and enthalpy drops between extraction points.

$$P_x = \sum_{k=1}^n Q_k (h_{in,k} - h_{out,k}) \quad (8)$$

giving $P_{HP} = 138.86$ MW, $P_{IP} = 178.80$ MW and $P_{LP} = 191.15$ MW. Hence $a_1 = 1.3765$, $a_2 = 1.2876$, $F_{HP} = 0.2729$, $F_{IP} = 0.3514$ and $F_{LP} = 0.3757$. The stage outputs sum to 508.8 MW, close to the 500 MW rating, which is a useful check on the HBD readings.

3.3 Hydro area

Area 2 is a single 500 MW hydro unit. The penstock–turbine combination is represented by the classical non-minimum-phase model [1, 5, 6].

$$G_h(s) = \frac{1-sT_w}{1+0.5sT_w}, T_w = \frac{LU}{gH} = \frac{LQ_r/(\pi r^2)}{gH} \quad (9)$$

where L is penstock length, U water velocity, Q_r rated discharge, r penstock radius and H rated head. For a penstock of $L = 96$ m and diameter 4 m carrying 72 m³/s, a water starting time of $T_w = 0.22$ s was adopted. The hydro governor is modelled as $1/(1 + sT_h)$ with $T_h = 1$ s, slower than the thermal governor because the wicket gates are servo-driven [1], [5]. The generator model is the same as in Area 1.

3.4 Tie-line and area control error

The areas are linked by a tie-line whose power deviation is [1, 3].

$$\Delta P_{tie,12}(s) = \frac{2\pi T_{12}}{s} [\Delta f_1(s) - \Delta f_2(s)] \quad (10)$$

with synchronizing coefficient $2\pi T_{12} = 0.545$ p.u. ($T_{12} = 0.0867$). Because Area 1 (1000 MW) is twice the size of Area 2, the area capacity ratio is $a_{12} = -P_{r1}/P_{r2} = -2$. The area control error is [2, 3].

$$ACE_i = \Delta P_{tie,i} + B_i \Delta f_i \quad (11)$$

where B_i is the frequency bias. Figure 2 shows the complete Simulink model. The switches in each area select either the unified or a conventional PID block, so that both configurations run on the same plant. Table 2 lists the parameters.

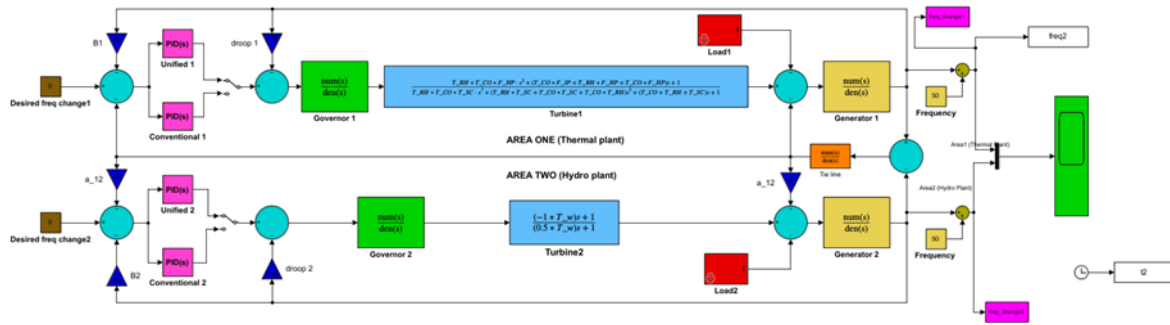


Figure 2. Simulink model of the two-area hydro–thermal system with unified PID control

Table 2. Parameters of the two-area hydro–thermal model

Area 1 (thermal)	Value	Area 2 (hydro) and tie-line	Value
Steam chest, T_{SC}	0.36 s	Water starting time, T_w	0.22 s
Reheater, T_{RH}	5.09 s	Hydro governor, T_h	1.0 s
Crossover, T_{CO}	0.40 s	Generator (K_p, T_p)	as Area 1
$F_{HP} / F_{IP} / F_{LP}$	0.2729 / 0.3514 / 0.3757	Synchronizing coeff., $2\pi T_{12}$	0.545 Pu.
Governor, T_g	0.25 s	Capacity ratio, a_{12}	–2
K_p / T_p	1 / 10 s	Rating	500 MW
Equivalent droop, R_{eq}	2.4 Hz/Pu.	Load step	1.0 Pu.
Rating	2×500 MW	Simulation time	100 s

4 CONTROLLER DESIGN AND TUNING

4.1 Unified PID controller and Z-N baseline

The secondary controller in each area is a parallel PID [7, 10],

$$C(s) = K_p + \frac{K_i}{s} + K_d s \quad (12)$$

placed ahead of the governor. It compares the measured frequency deviation with a zero reference and adjusts the governor set-point. In the unified scheme, the same (K_p, K_i, K_d) is applied in both areas, so the optimiser searches a three-dimensional rather than a six-dimensional space. For the baseline, K_i and K_d were set to zero and K_p raised until both areas oscillated steadily. This occurred at the critical gain $K_c = 27.8$, with period $DT = 9.589$ s ($f_0 = 0.1043$ Hz). The same K_c and F_0 appeared in both areas, which is consistent with their coupling through the tie-line. Following the Z-N rules [8], $K_p = 0.6K_c = 16.68$, with integral and derivative settings of $2 \times F_0 = 0.2086$ and $0.125/F_0 = 1.1985$.

4.2 PSO tuning

Each particle's position is a candidate gain triple. Velocity and position are updated as [9, 19].

$$v_{ij}^{t+1} = w v_{ij}^t + c_1 r_1 (pbest_{ij}^t - x_{ij}^t) + c_2 r_2 (gbest^t - x_{ij}^t) \quad (13)$$

$$x_{ij}^{t+1} = x_{ij}^t + v_{ij}^{t+1} \quad (14)$$

Where w is the time-varying inertia weight [19] given by $w = k \times (0.9 - 0.8 \times (\frac{iter-1}{maxit-1}))$, are the cognitive and social coefficients, and r_1, r_2 are uniform random numbers in $[0, 1]$. A swarm of 30 particles was used, each gain being bounded to $[1, 50]$. The upper bound came from manual trials, which showed that gains above 50 produced violent responses that would not be acceptable on a real plant. Iterations stopped when all particles had converged on the global best. Each particle was evaluated by running the full Simulink model and computing the ITAE of both area frequency deviations [10, 11],

$$J = \int_0^T t (|\Delta f_1(t)| + |\Delta f_2(t)|) dt \quad (15)$$

using the trapezoidal rule (**trapz**) on logged simulation data, with $T = 100$ s. Time weighting penalises errors that persist late in the response, so ITAE discourages both slow settling and residual offset [7, 10].

4.3 Hybrid PSO–MPC scheme

In the hybrid scheme, an MPC block from the MATLAB Model Predictive Control Toolbox is connected alongside the PID loop [26] (Figure 3). The governor command is the manipulated variable, the load step is a measured disturbance, and the generator frequency is the measured output, with a zero reference. At each sample (with a sample time of 1.0s), the MPC minimizes a quadratic cost of the form (16).

$$\min_{\Delta u} \sum_{k=1}^{N_p} \|r(k) - y(k)\|_Q^2 + \sum_{k=0}^{N_c-1} \|\Delta u(k)\|_R^2 \quad (16)$$

Over prediction horizon $N_p = 20$ and control horizon $N_c = 2$. (using state weight $Q = 1$ and control effort weight $R = 0.1$)) When it was tested alone against its internal plant model, the MPC settled a unit step in about 6 s. PSO then tuned the PID gains with the MPC in the loop, using the same swarm, bounds and cost function as in Section 4.2. The PID gains found in this way therefore account for the predictive action rather than being tuned in isolation [26].

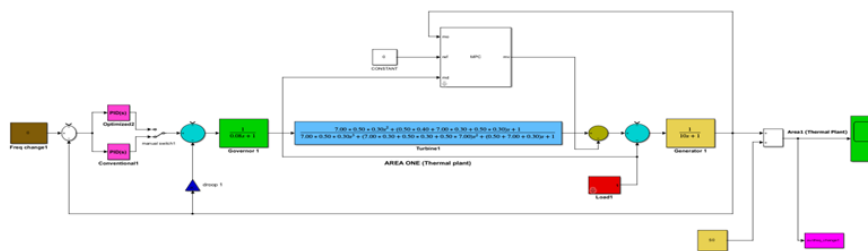


Figure 3. PID and MPC controllers connected to the thermal area

5. RESULTS AND DISCUSSION

All simulations ran for 100 s in MATLAB/Simulink R2023b, with a 1.0 Pu. step load applied at $t = 20$ s. With no disturbance, both area frequencies stayed flat at 50 Hz, confirming that the model initializes at equilibrium.

5.1 Baseline behaviour

Under Z-N tuning the system remained stable for a step in Area 1, in Area 2, and in both areas together, but in no case did the frequency return to 50 Hz, consistent with earlier reports on classically tuned controllers [7, 8]. The offset was about 0.009 Hz after a disturbance in Area 1 and about 0.005 Hz after one in Area 2. The hydro area consistently responded more slowly than the thermal area, which reflects its larger governor time constant and the initial power reversal of the penstock [1, 5].

5.2 Optimization results

Figure 4 shows the convergence of the ITAE cost and Table 3 the resulting gains. Standard PSO settled on (28,14,40) with $J = 422.18$; the cost curve was essentially flat by about the tenth iteration, and all particles had converged by iteration 21 after 9.5 min. PSO-MPC settled on (30,18,50) with $J = 297.99$, converging by iteration 26 after 29.9 min. This rapid early flattening of the cost is typical of PSO-based LFC tuning [9, 10]. The hybrid cost is 70.6% of the PSO cost, a reduction of 29.4%. That reduction comes at roughly three times the offline run time, which is acceptable because tuning is carried out once and does not affect real-time operation, in contrast with standalone MPC which solves an optimization at every sample [26]. The derivative gain of the hybrid solution sits on the upper search bound of 50. This suggests the optimum may lie just outside the range explored, and a slightly wider bound, subject to actuator limits, is worth testing [11].

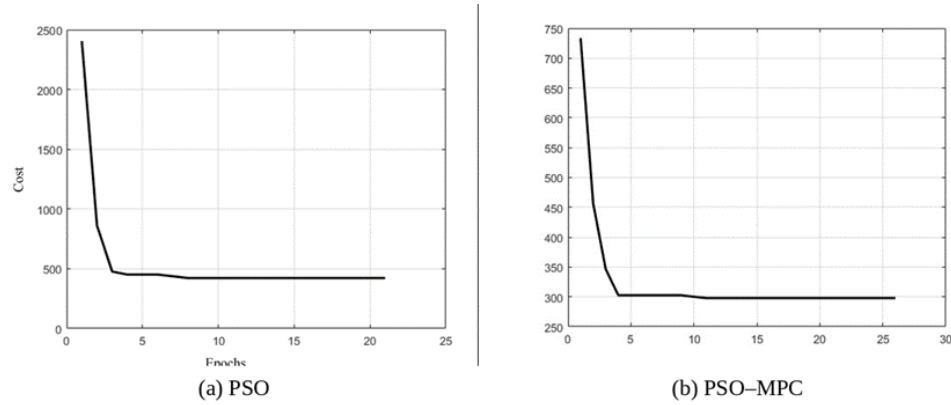


Figure 4. Convergence of the ITAE cost: (a) standard PSO; (b) hybrid PSO-MPC

Table 3. Controller gains and optimization results

Tuning method	K_p	K_i	K_d	ITAE cost J	Iterations	Run time (min)
Z-N (baseline)	16.68	0.2086	1.1985	—	—	—
Standard PSO	28	14	40	422.18	21	9.5
Hybrid PSO-MPC	30	18	50	297.99	26	29.9

5.3 Comparative dynamic response

Figures 5 and 6 compare the three controllers for a disturbance in Area 1 and Area 2 respectively. Both optimized controllers return the frequency in both areas to 50 Hz, whereas the baseline settles at an offset. For the Area 1 disturbance, the optimized controllers also reduce the Area 1 frequency dip visibly, from roughly 0.021 Hz under Z-N to about 0.016 Hz. Similar reductions in peak deviation and the elimination of residual offset have been reported for metaheuristically tuned PID controllers in multi-area systems [10, 11, 25].

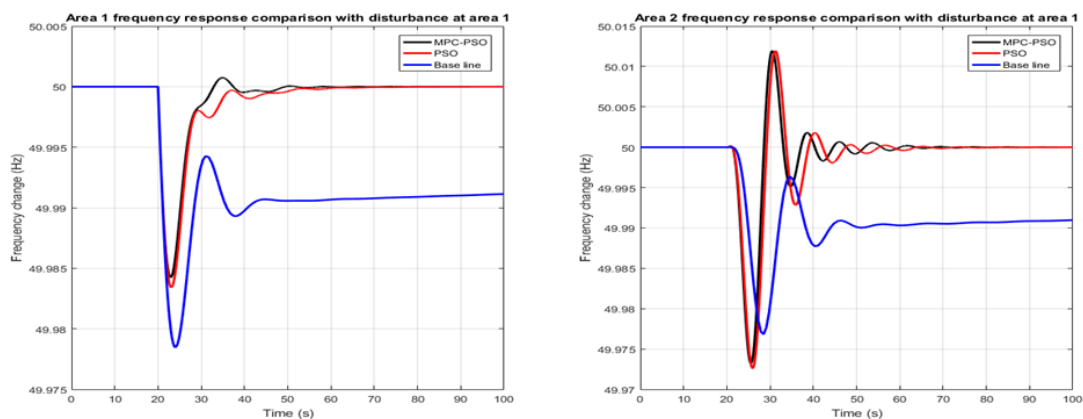


Figure 5. Frequency response with 1.0 Pu. load step in Area 1: (a) Area 1; (b) Area 2

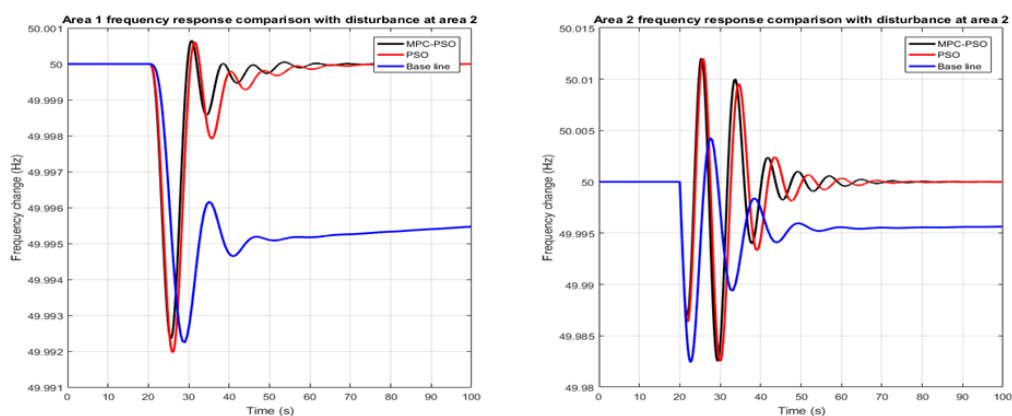


Figure 6. Frequency response with 1.0 Pu. load step in Area 2: (a) Area 1; (b) Area 2

Table 4 gives the transient indices for the Area 2 disturbance.

Table 4. Transient performance for a 1.0 Pu. load step in Area 2 (deviations in Hz; settling instant on the simulation clock, step at $t = 20$ s)

Area	Controller	Overshoot	Undershoot	Settling instant (s)	Steady-state error
Area 1	PSO-MPC	0.0007	0.0076	60	0
	PSO	0.0007	0.0080	60	0
	Z-N	0	0.0078	65	0.005
Area 2	PSO-MPC	0.012	0.017	65	0
	PSO	0.012	0.017	65	0
	Z-N	0.004	0.017	55	0.005

The clearest effect of optimization is the removal of the steady-state error, and with it the persistent ACE of about 0.005 that the baseline leaves behind [2, 3]. In Area 1, PSO and PSO-MPC settle about 5 s sooner than Z-N, and PSO-MPC gives the smallest undershoot (0.0076 Hz against 0.0080 Hz for PSO). Elsewhere the two optimized controllers are nearly indistinguishable, which is plausible given that their gains differ only modestly and the tie-line couples the two areas strongly. The baseline's earlier "settling" in Area 2 should be read with care: it settles quickly only because it stops at an offset rather than returning to 50 Hz. The optimized controllers do pay for zero offset with a larger first overshoot in the hydro area (0.012 Hz against 0.004 Hz), a consequence of higher gains acting on a plant whose initial response is reversed [5, 6]. Taken together, the results support the use of a single coordinated gain set. One triple of gains, tuned once, restored nominal frequency in both a thermal and a hydro area without area-specific adjustment and without the two controllers opposing each other across the tie-line. The ITAE reduction from PSO-MPC is substantial, but its benefit in peak deviation is small. It is best viewed as a refinement of PSO tuning rather than a qualitatively different controller. Some limitations should be noted. The model is linear and omits generation-rate constraints, governor dead-band and the transient-droop compensation normally fitted to hydro governors, all of which would influence the achievable gains [6, 30]. Only step disturbances of one size were tested. The PSO population was chosen by trial, and a poor choice led to stagnation in local minima during development.

6 CONCLUSIONS

A unified PID load frequency controller was developed for a two-area hydro-thermal system consisting of two 500 MW reheat steam units and one 500 MW hydro unit. The steam-turbine time constants and power fractions were derived from a plant heat balance diagram and steam tables rather than assumed, giving $T_{SC} = 0.36$ s, $T_{RH} = 5.09$ s, $T_{CO} = 0.40$ s and stage fractions of 0.273, 0.351 and 0.376. Z-N tuning kept the system stable but left a frequency offset of 0.005–0.009 Hz. Standard PSO and hybrid PSO-MPC tuning both eliminated this offset and returned the frequency to 50 Hz in both areas. The hybrid scheme lowered the ITAE cost from 422.18 to 297.99 (29.4%) and gave the smallest Area 1 undershoot, though its transient gains over standard PSO were marginal. Future work should include generation-rate constraints and governor nonlinearities, random and multi-step load patterns, a wider gain range, and alternative tuners such as adaptive neuro-fuzzy inference systems that avoid manual selection of swarm size.

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