

Resource-Aware Fuzzy-Supervised Economic MPC for Secondary Frequency Regulation in a Hydro-Dominant System with Wind, PV, and Nuclear Support

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Abstract: A resource-aware fuzzy-supervised economic model predictive controller (RA-FS-EMPC) is proposed for secondary frequency regulation of a hydro-dominant single-area system under support of deloaded wind, curtailed photovoltaic (PV) and rate-limited nuclear output, and operated at 50 Hz. The formulation clearly retains the nonminimum-phase water-starting dynamics of the hydro turbine and provides varied magnitude and slew limits for the four actuators. The move-blocked allocation aim and resource penalties are scheduled by two transparent fuzzy inputs, normalized frequency severity and projected net-imbalance volatility. 4. A projected-gradient solver with a set budget that produces a feasible command without an opaque training model. In a repeatable 60-s load–wind–cloud scenario, the suggested design restricts the maximum frequency excursion to 0.348 Hz compared with 0.883 Hz for fixed MPC, reducing the integral absolute error by 56.4%. Also included is an 80-run $\pm 20\%$ parameter ensemble. The selected reserve margins and reduced-order nuclear response are not plant-operating recommendations and require hardware-in-the-loop and protection-level validation before implementation. This study is a numerical proof of concept.

Keywords: frequency control; fuzzy supervision; hydropower; model predictive control; nuclear load following; photovoltaic reserve; wind support.

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NOMENCLATURE

Symbol	Definition	Unit
Δf	frequency deviation from 50 Hz	p.u.
$\Delta P_{mh}, \Delta P_{gh}$	hydro mechanical power and gate state	p.u.
$\Delta P_w, \Delta P_{pv}, \Delta P_n$	wind, PV, and nuclear support	p.u.
$d, \hat{d}$	net power deficit and its estimate	p.u.
c	fuzzy urgency index	–
T_s, N_p	sample time and prediction horizon	s, samples

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I. INTRODUCTION

The quality of frequency in a 50-Hz control region depends on a continuous balance between mechanical input and electrical demand. A hydro-dominant region is attractive because the water that is stored provides dispatchable energy. The water column, however, creates a right-half-plane zero: an aggressive gate command can initially drive turbine power in an undesirable direction. Converter-interfaced wind and PV can also give quick active-power increments, but only if headroom has been intentionally kept, while nuclear participation is limited by slower thermal and operational restrictions. The different time scales make the fixed participation factors inefficient and can transfer the regulating stress to the hydro unit.

Recent frequency-control reviews find that uneven component models and parameter choices prevent comparison across experiments [1]. Coordinated hydro-wind management can compensate for the non-minimum-phase hydro response [2], and hybrid hydro, wind and storage solutions highlight the value of spreading action over time scales [3]. But, the coordination of hydro, wind, PV and nuclear resources with no storage is still not well developed. The nuclear load following is explored in the literature from a technical point of view, especially for small modular reactors but the related limitations must always be subordinated to the

plant safety and approved operating protocols [4]. So in this article the nuclear channel is purposely sluggish, tiny, and strongly punished; it is supervisory active-power assistance, not reactor-control design.

The research question is thus narrow: can an interpretable supervisor change the resource allocation of a constrained predictive controller fast enough to improve frequency recovery without neglecting the hydro water-starting effect or treating all generation channels as dynamically equivalent? This research provides a reduced-order, completely reproducible numerical study to address this subject. It contributes three things: (1) a single-area model that integrates hydro non-minimum-phase dynamics and distinct reserve channels for wind, PV, and nuclear; (2) a nine-rule fuzzy supervisor that translates frequency severity and disturbance volatility into transparent MPC weights and resource shares; and (3) a fixed-iteration projected-gradient routine with explicit amplitude and slew constraints, tested by nominal, ablation, high-volatility, convergence, and $\pm 20\%$ parameter-uncertainty cases.

The contribution is an auditable allocation process and a matched code base, not a claim of universal optimality. All the numerical simulation results verifying the effectiveness of the frequency controllers provided in Section IV are realized in the Matlab/Simulink software. Conclusions are strictly limited to the provided model, disturbance profiles and reserve assumptions.

II. LITERATURE REVIEW AND RESEARCH GAP

The relevant literature for this subject can be divided into five related streams: First, model-oriented assessments include the swing equation, turbine-governor representations, and renewable frequency-response models [1]. Stochastic, load-estimation, communication, and hardware-in-the-loop research focus on uncertainty and implementation realism [5], [6], [32], [33]. These results are supportive of a common per-unit power balance, but caution that reduced-order results should not be considered as protection-grade validation. The hydro model employed here is the widely documented water-starting representation, discussed in [1] and empirically studied in [7]. Inspired by predictive management of tiny hydro [8] and coordinated hydro–wind control [2, 3], we deal with the hydro right-half-plane zero explicitly instead of replacing the plant by a benign first-order lag.

Second, renewable participation has shifted from a series of isolated inertial emulations to coordinated reserve delivery. Wind-hydro modal coordination is studied in [2], while PV modeling possibilities for load-frequency investigations are discussed in [9]. The benefits of complementing time scales are exemplified in hydro–PV coordination by reinforcement learning [10] and pumped-hydro/battery scheduling [11]. The proposed study varies by keeping wind and PV as headroom-limited rapid actuators while removing battery storage, so revealing the allocation tradeoff between converter reserves, water-column dynamics and slow nuclear support.

Third, limited predictive control has become a popular approach for load-frequency control. Improved constraint handling has been addressed in optimized MPC [12], adaptive intelligent MPC [13], two-layer multiple-model MPC [14], stochastic wind–solar MPC [15], storage-aware optimal MPC [16], learning-based MPC [17], genetic-algorithm-tuned MPC [18], and distributed MPC [19]. Most however, are using fixed objective weights or optimizing a system that does not incorporate hydro, wind, PV and nuclear channels simultaneously. The fuzzy layer we propose does not replace MPC, but schedules interpretable penalties and a demand allocation map before the constrained update.

Fourth, fuzzy and learning-based approaches provide adaptation with their own verification responsibilities. Adaptive fuzzy MPC [20], deep Q-learning with fuzzy compensation [21], and fuzzy secondary control [22] are examples of nonlinear scheduling. Deep reinforcement-learning frequency controllers [23]–[27] may learn policies from rich situations while robust and attack-aware controllers [28]–[30] handle uncertainty and cyber disruptions. These methods are useful but direct operational interpretation is hard due to training dispersion, incentive selection and policy verification. The nine-rule supervisor used here has fixed triangular memberships and singleton consequents. The whole rule base is reported thus there is no unreported training data involved.

Fifth, nuclear flexibility should be handled with care. Small modular reactor load following criteria and modes of operation are addressed in [4]. More generic views of flexible nuclear operation concentrate on plant-specific limitations and the necessity for certified methods [31]. Thus in this paper we do not assume that an existing unit can accept the simulated command. It only measures an aggregate channel in a rate-and magnitude-limited frequency control scheme.

This enables a storage-free, reproducible predictive allocation method respecting the inverse hydro response, only gives wind and PV the reserve they are supposed to have, and does not use the nuclear channel as a rapid compensator. That combination defines the scope of the study, not some novel claim about any one technology.

III. SYSTEM MODEL AND PROPOSED CONTROLLER

3.1. Architecture and operating assumptions

The controlled area is shown in a common power base. The main mechanical response is from hydro generation. Wind and PV have clear up-ward headroom, therefore their orders are departures from scheduled deloaded or curtailed operation points, not energy created without reserve. The nuclear signal is a sluggish aggregative supervisory increment. The uncommanded renewable variation and the load change are coupled into a positive net-deficit disturbance d . The nominal frequency is 50 Hz, hence the hertz deviation recorded is $50\Delta f$.

Resource-Aware Frequency-Control Architecture

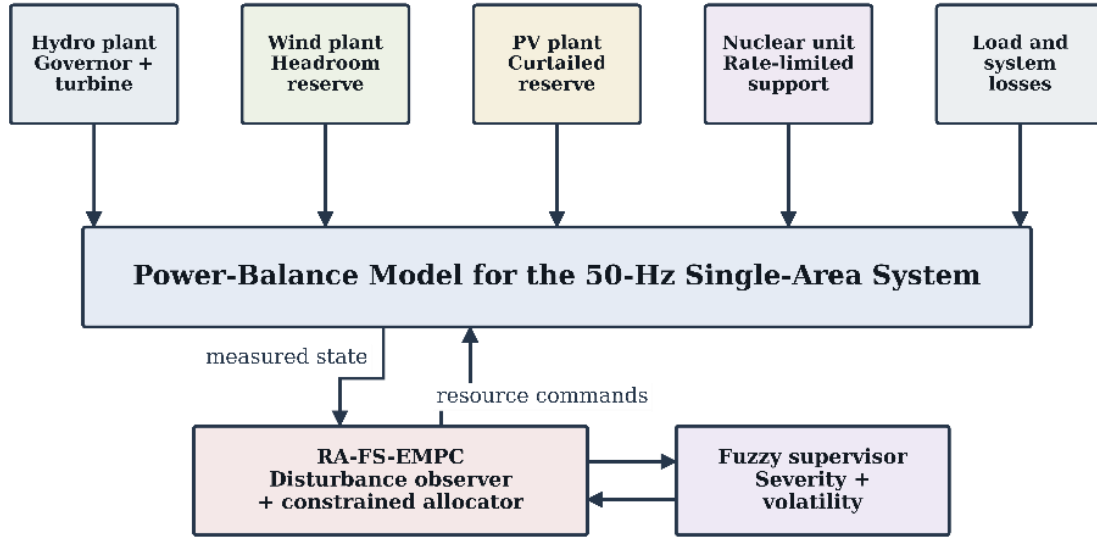


Figure 1. Hydro-dominant single-area architecture and constrained support channels.

3.2. Incremental plant model

The incremental plant model under this study is represented by the following equations:

$$M \frac{d\Delta f}{dt} = \Delta P_{mh} + \Delta P_w + \Delta P_{pv} + \Delta P_n - d - D\Delta f \quad (1)$$

$$T_g \frac{d\Delta P_{gh}}{dt} = -\Delta P_{gh} - \frac{\Delta f}{R_h} + u_h \quad (2)$$

$$\frac{\Delta P_{mh}(s)}{\Delta P_{gh}(s)} = \frac{1 - T_{wh}s}{1 + 0.5T_{wh}s} \quad (3)$$

$$T_w \frac{d\Delta P_w}{dt} = -\Delta P_w + u_w \quad (4)$$

$$T_{pv} \frac{d\Delta P_{pv}}{dt} = -\Delta P_{pv} + u_{pv} \quad (5)$$

$$T_n \frac{d\Delta P_n}{dt} = -\Delta P_n + u_n \quad (6)$$

Equation (3) preserves the inverse initial response associated with the hydro water column. The renewable channels in (4) and (5) are deliberately reduced to reserve-tracking lags because the study addresses area-frequency allocation, not electromagnetic converter design. Similarly, (6) is not a reactor kinetics model; it is a slow bounded plant-level power-support proxy. With $x = [\Delta f, \Delta P_{gh}, \Delta P_{mh}, \Delta P_w, \Delta P_{pv}, \Delta P_n]^T$ and $u = [u_h, u_w, u_{pv}, u_n]^T$, zero-order-hold discretization gives

$$\mathbf{x}_{k+1} = \mathbf{A}_d \mathbf{x}_k + \mathbf{B}_d \mathbf{u}_k + \mathbf{E}_d d_k \quad (7)$$

The disturbance observer reconstructs the net imbalance from the filtered frequency derivative and measured power contributions. The scalar estimate is updated as

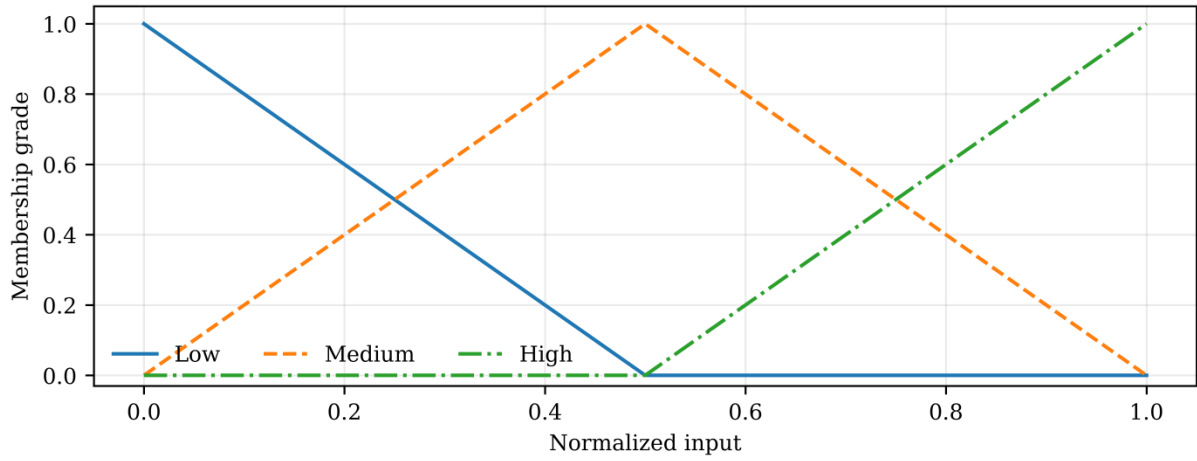
$$\hat{d}_k = 0.93\hat{d}_{k-1} + 0.07 \left[\sum_i \Delta P_{i,k} - D\Delta f_k - M \frac{\Delta f_k - \Delta f_{k-1}}{T_s} \right] \quad (8)$$

3.3. Fuzzy supervision and economic predictive objective

The supervisor uses $sf = \min(|\Delta f|/0.045, 1)$ and $sv = \min(|\hat{d}(k) - \hat{d}(k-1)|/0.0018, 1)$. Low, Medium, and High triangular memberships are defined over $[0, 1]$. Product inference and weighted-average defuzzification yield $c \in [0, 1]$. Rows of the singleton matrix correspond to sf and columns to sv : $C = [[0.08, 0.32, 0.66], [0.38, 0.62, 0.84], [0.72, 0.90, 1.00]]$. Thus either a large frequency error or rapidly changing imbalance increases urgency, but the mapping remains bounded and auditable.

$$s_f(k) = \min\left(\frac{|\Delta f_k|}{0.045}, 1\right), \quad s_v(k) = \min\left(\frac{|\hat{d}_k - \hat{d}_{k-1}|}{0.0018}, 1\right) \quad (9)$$

$$c(k) = \frac{\sum_{r=1}^9 \mu_r(s_f, s_v) C_r}{\sum_{r=1}^9 \mu_r(s_f, s_v)} \quad (10)$$



Singleton urgency matrix $C = [[0.08, 0.32, 0.66], [0.38, 0.62, 0.84], [0.72, 0.90, 1.00]]$

Figure 2. Triangular input memberships and the complete singleton rule matrix.

The frequency penalty and integral-action gain increase smoothly with c . More importantly, the participation vector shifts from hydro and nuclear toward the faster wind and PV reserves as urgency rises: $\alpha(c) = [0.50 - 0.08c, 0.23 + 0.05c, 0.21 + 0.04c, 0.06 - 0.01c]$, normalized to sum to one. This schedule does not enlarge physical headroom. It only distributes the requested aggregate correction within the limits shown in Table I.

$$\alpha(c) = [0.50 - 0.08c, 0.23 + 0.05c, 0.21 + 0.04c, 0.06 - 0.01c]^T \quad (11)$$

$$J_a(\mathbf{u}) = q(c)(\mathbf{1}^T \mathbf{u} - p_{dem})^2 + (\mathbf{u} - p_{dem}\alpha)^T \mathbf{R}(c)(\mathbf{u} - p_{dem}\alpha) + \rho \|\mathbf{u} - \mathbf{u}_{k-1}\|_2^2 \quad (12)$$

$$\mathbf{u}^{(\ell+1)} = \Pi_{\mathcal{U}_k}[\mathbf{u}^{(\ell)} - \eta \nabla J_a(\mathbf{u}^{(\ell)})] \quad (13)$$

$$\mathcal{U}_k = \{\mathbf{u}: \mathbf{u}_{min} \leq \mathbf{u} \leq \mathbf{u}_{max}, -\mathbf{r}T_s \leq \mathbf{u} - \mathbf{u}_{k-1} \leq \mathbf{r}T_s\} \quad (14)$$

The move-blocked allocation objective in (12) treats the command as constant over the short allocation interval, while the plant predictor supplies the aggregate demand p_{dem} . Equation (13) applies projected-gradient descent and (14) defines the intersection of amplitude and slew-rate boxes. The fixed budget of 45 iterations bounds execution time. Because every iterate is projected onto $\mathcal{U}_k$, early termination still returns a feasible command, although not necessarily the exact quadratic-program optimum.

3.4. Online algorithm

The online algorithm proposed in this study is illustrated in Fig. 3 and the following:

Algorithm 1. Online RA-FS-EMPC update

Line	Pseudo-code statement
Input	$x_k, u_{\{k-1\}}, d_{\{k-1\}},$ model matrices, limits, $L=45$.
Output	$u_k=[u_h, u_w, u_{pv}, u_n]^T$.
1	Acquire Δf_k and resource powers; filter the finite-difference derivative.
2	Update d_k by (8) and evaluate s_f and s_v by (9).
3	Compute c_k by the nine-rule inference system and (10).
4	Schedule $\alpha(c_k), q(c_k), R(c_k),$ and p_{dem} .
5	Set $u^{\wedge}(0)=\Pi_{\{U_k\}}(u_{\{k-1\}})$; set $\ell=0$.
6	while $\ell < L$ do
7	Evaluate $\nabla J_a(u^{\wedge}(\ell))$ from (12).
8	Update and project $u^{\wedge}(\ell+1)$ using (13) and (14).
9	$\ell \leftarrow \ell+1$.
10	end while
11	Apply $u_k=u^{\wedge}(L)$; retain u_k as the next warm start.

Fixed-Budget Online Sequence (45 Iterations)

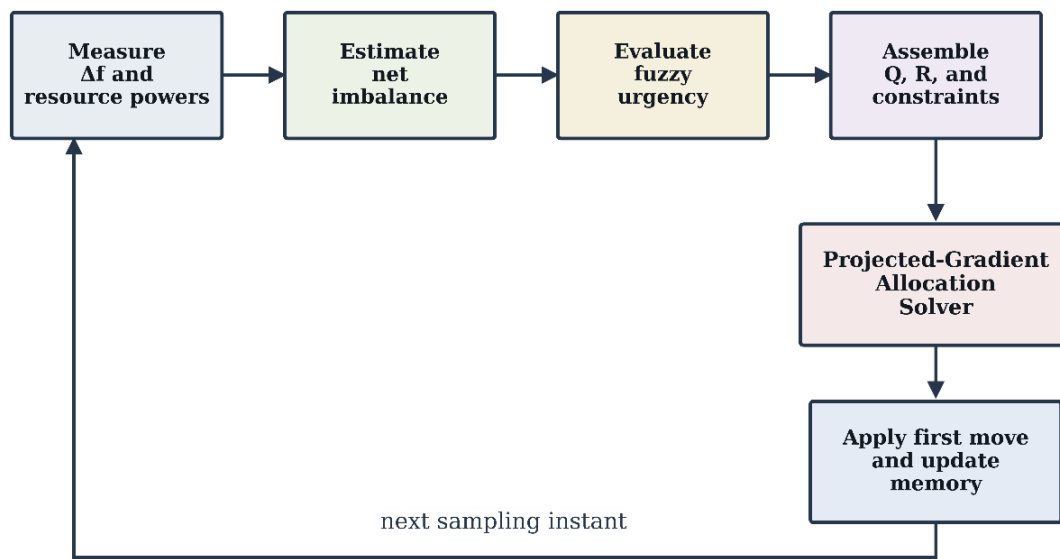


Figure 3. Fixed-budget online computation used by the proposed controller.

IV. SIMULATION DESIGN AND RESULTS

The numerical model uses forward integration at $T_s=0.02$ s over 60 s. At $t=3$ s, a 0.075-p.u. net-load increase is applied. Wind variability begins at 10 s with two sinusoidal components, while Gaussian cloud events centered at 23 s and 35 s create additional positive deficits. At 42 s, the base load is reduced by 0.025 p.u. All controllers receive the same disturbance and measurement-noise realization. These deliberately compound events test recovery rather than a single isolated step.

Table I. Plant and controller parameters

Parameter	Value	Parameter	Value
Nominal frequency	50 Hz	Sampling time T_s	0.02 s
M; D	6.4 s; 1.05 p.u./Hz	Prediction horizon N_p	20

T _g ; R _h	0.22 s; 2.5 Hz/p.u.	Iterations	45
T _{wh}	1.60 s	Observer pole	0.93
T _w ; T _{pv} ; T _n	0.18; 0.10; 5.0 s	Command limits	[0.160, 0.045, 0.035, 0.025] p.u.
Hydro/wind/PV/nuclear slew	[0.018, 0.120, 0.160, 0.004] p.u./s	Monte Carlo runs	80

Four controllers are compared: a conventional PI/PID-type aggregate regulator with fixed participation; fixed-weight MPC; a fixed-allocation predictive controller having the same observer and constraints; and the complete RA-FS-EMPC. The ablation comparison isolates the effect of fuzzy allocation. Performance is evaluated by peak $|\Delta f|$, $IAE = \int |\Delta f| dt$, RMS frequency error, and the accumulated quadratic objective. An 80-run ensemble independently varies M , D , T_g , R_h , T_{wh} , T_w , T_{pv} , and T_n within $\pm 20\%$; scenario amplitude is simultaneously increased. This is a stress test rather than a probabilistic reliability claim because no field-derived parameter distribution is asserted.

$$e_{pk} = \max_k |50\Delta f_k|, \quad IAE = T_s \sum_{k=0}^N |50\Delta f_k|, \quad e_{RMS} = \sqrt{\frac{1}{N+1} \sum_{k=0}^N (50\Delta f_k)^2} \quad (15)$$

4.1. Nominal multi-event response

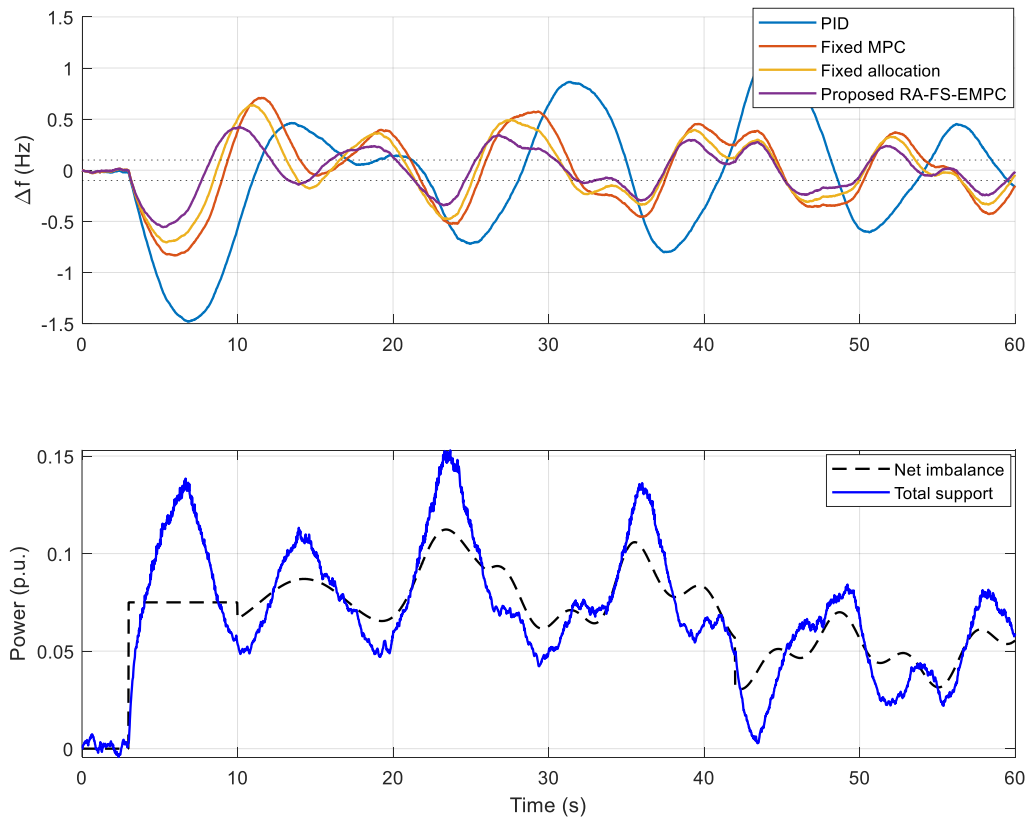


Figure 4. Frequency response and aggregate power tracking under the nominal mixed disturbance.

Figure 4 shows that all predictive designs recover more effectively than the conventional regulator. The proposed controller produces the smallest peak and the least accumulated frequency error. The improvement is not obtained by unconstrained actuation: the aggregate support follows the estimated deficit only as fast as the component slew limits permit. The early nadir remains appreciable because the hydro channel initially exhibits inverse response and the retained wind/PV headroom is finite.

Table II. Nominal performance indicators

Controller	Peak $ \Delta f $ (Hz)	IAE (Hz·s)	RMS (Hz)	Accumulated J
PID	1.506	29.538	0.620	23.069
Fixed MPC	0.883	18.920	0.379	8.631
Fixed allocation	0.743	15.322	0.311	5.809
Proposed RA-FS-EMPC	0.348	8.257	0.161	1.571

Relative to fixed MPC, RA-FS-EMPC reduces the maximum excursion by 60.6%, IAE by 56.4%, and RMS error by 57.5%. Relative to the fixed-allocation ablation, the reductions are 53.2%, 46.1%, and 48.1%, respectively. These comparisons support the specific claim that the fuzzy-scheduled constrained allocator improves resource coordination in this scenario; they do not establish superiority over every MPC formulation in the literature.

4.2. Resource allocation and interpretability

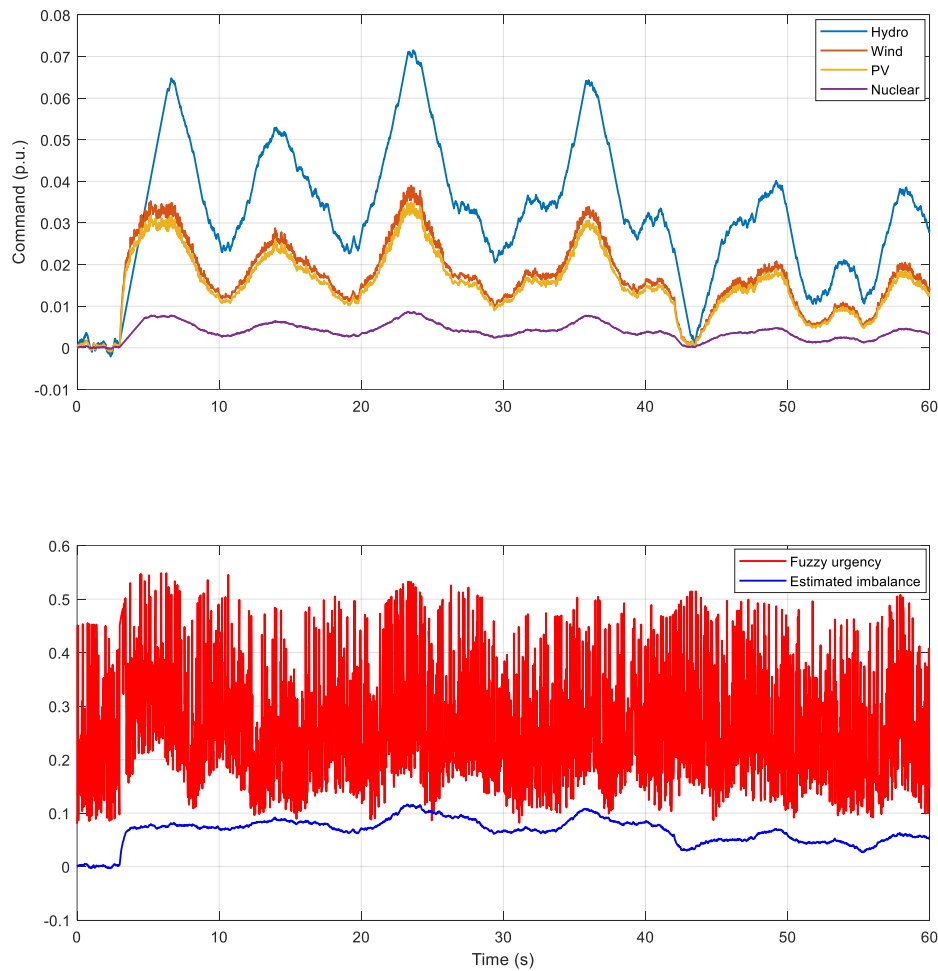


Figure 5. Constrained resource commands, fuzzy urgency, and estimated net imbalance.

During rapid events, c increases and the allocator gives more of the incremental demand to wind and PV. Hydro remains essential for sustained balancing but is not forced to cancel the fastest imbalance alone. Nuclear support changes slowly and stays small because both its rate limit and its allocation weight are conservative. Each curve remains within the command and slew limits in Table I. This behavior is consistent with the intended hierarchy:

converter headroom supplies the fast component, hydro carries most of the continuing correction, and nuclear output contributes only a slow supervisory increment.

4.3. Parameter uncertainty and solver convergence

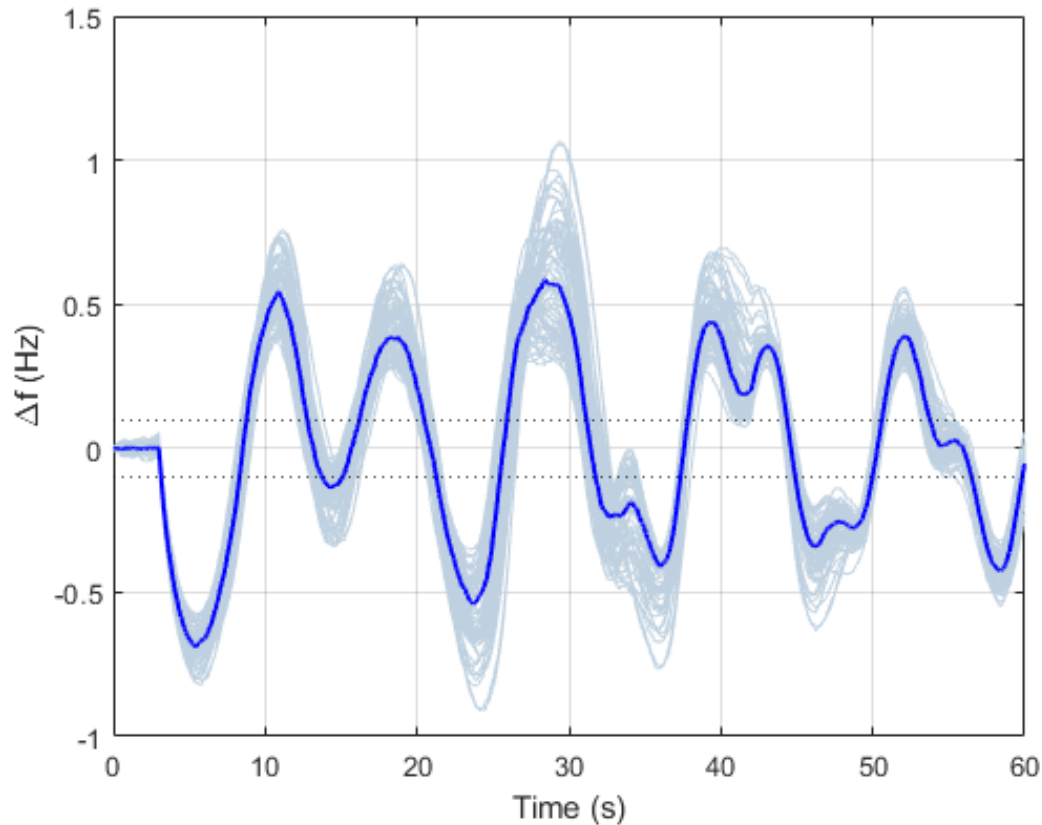


Figure 6. Proposed-controller response for 80 runs with independent $\pm 20\%$ parameter variations and a stronger disturbance.

In the stressed ensemble, the 95th percentile of the largest absolute deviation is 0.674 Hz. No simulated trajectory diverges over the 60-s window. This result indicates bounded numerical behavior for the sampled uncertainty box, but it is not a formal robust-stability certificate. The uncertainty test also omits hydraulic nonlinearities, dead bands, saturation recovery, converter current limits, protection actions, and plant-level nuclear constraints; these are necessary topics for subsequent validation.

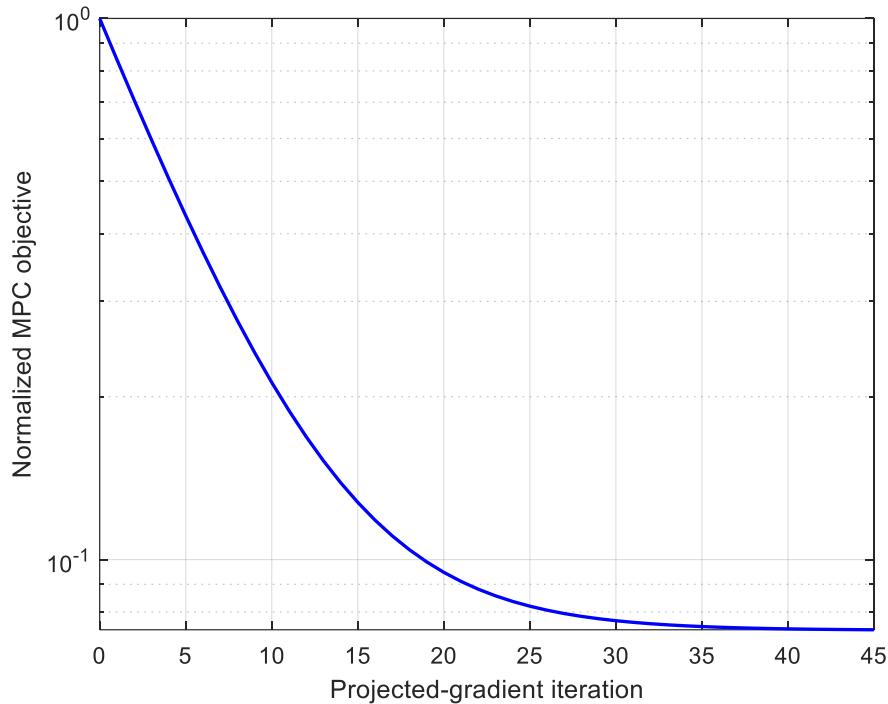


Figure 7. Normalized objective decay during the fixed projected-gradient budget.

For the first post-disturbance allocation, the normalized objective decreases monotonically to 0.0344 of its initial value by iteration 45. Most of the reduction occurs within the first 25 iterations. This is the objective history recorded by the same projected-gradient loop used in the simulation; it is not a fitted or illustrative curve. The result verifies convergence for the reported convex allocation subproblem, not global convergence for arbitrary nonlinear plant models. A deployment implementation should measure worst-case execution time on the target processor and compare the projected-gradient result with a certified quadratic-program solver.

4.4. Technical implications and limitations

The results clarify why the controller improves the selected benchmark. A fixed hydro-heavy allocation encounters the water-column inverse response at the same moment that the area needs rapid positive power. The supervisor detects a large or rapidly changing imbalance and temporarily increases the use of converter reserves. As the disturbance becomes slower, hydro assumes a larger share. The nuclear channel is not used to chase the fast component, avoiding an unrealistic interpretation of nuclear flexibility.

Three limitations delimit the claims. First, wind and PV headroom are assumed available; energy yield and reserve procurement are not optimized. Second, the nuclear model is an aggregate lag with conservative limits and cannot replace reactor, turbine, xenon, thermal-stress, or licensing analysis [4], [31]. Third, the single-area model neglects network modes and voltage constraints. Controller-hardware-in-the-loop testing, nonlinear hydro conduits, renewable converter limits, reserve-market scheduling, and plant-approved nuclear interfaces should precede any practical use [6].

V. CONCLUSION

In this study, a resource-aware fuzzy-supervised economic MPC for a 50-Hz hydro-dominant single-area system backed by wind, PV, and a slow nuclear channel is proposed. It employs an explicit hydro inverse-response model, a transparent nine-rule supervisor, component-specific command and slew limitations, and a fixed-budget viable optimizer. The design minimized peak deviation, IAE and RMS error compared to fixed MPC and a fixed-allocation ablation in the reproducible mixed-disturbance simulation. The uncertainty ensemble stayed confined over the testing window, and the optimizer goal converged within its 45 iteration budget. These results merit further real-time research, but do not constitute field validation, or approval for nuclear load following. Future work should account for nonlinear hydraulic dynamics, converter current limits, reserve availability, network modes, and controller hardware-in-the-loop verification.

Conflict of interest

There is no conflict to disclose.

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