

# The FiBSR Method for Face Super-Resolution Reconstruction in Power Systems

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**Abstract:** This paper proposes a blind face super-resolution reconstruction method called FiBSR, aiming to solve the complex spatial-temporal degradation problems in real scenarios. The core innovations of this method include: A physical modeling system based on anisotropic Gaussian kernels is constructed, and the degradation prior of spatial changes is explicitly regressed through the degradation kernel parameter estimation network (SV\_KEN), a multi-scale discriminator, and a progressive two-stage training strategy, FiBSR provides a robust and systematic solution that outperforms existing mainstream methods in both subjective and objective evaluations, laying a solid foundation for practical applications in complex degradation scenarios.

**Keywords:** Face Super-Resolution, Spatially Variant Degradation, Power Systems.

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## 1. Practical Challenges of Face Super-Resolution in Power Systems

As a critical research task in computer vision, the importance and challenges of face super-resolution (FSR) primarily stem from the highly specific nature of facial images [1]. Compared to general natural images, human faces possess a stable and explicit structural composition; for instance, key facial components such as eyes, noses, and mouths exhibit strong prior constraints in their spatial layout [2,3], accompanied by rich and subtle textural variations. This dual attribute of "strong structure and high detail" dictates that FSR must not only restore a high-resolution appearance but also strictly preserve semantic consistency and identity-discriminative information during the reconstruction process [4,5]. Any structural deviation or erroneous texture reconstruction can directly compromise face recognition accuracy and perceptual credibility.

Seasonal electricity imbalance in power systems has become a prominent contradiction in the energy transition. The "double-peak" characteristic formed by summer air conditioning cooling loads and winter heating loads leads to a continuously expanding peak-valley difference. In 2023, the national peak load reached 1.39 billion kW, creating enormous seasonal regulation pressure. The mismatch between the output characteristics of renewable energy sources ("wind shortage in summer, solar shortage in winter") and load demand exacerbates the supply-demand contradiction. Existing regulation resources such as pumped hydro storage and electrochemical energy storage can only meet daily regulation needs, with severe deficiencies in cross-seasonal regulation capabilities. Simultaneously, cross-regional power transmission channel capacity is limited, and market mechanisms are imperfect, making it difficult to achieve optimal allocation of seasonal electricity. The frequent occurrence of extreme weather further amplifies this contradiction, posing a severe challenge to the safe and stable operation of the power system.

## 2. Core Role of Optimization Algorithms in Energy Storage System Dispatch and Limitations of Existing Algorithms

Optimization algorithms play a core role in energy storage system dispatch, mainly reflected in three aspects: first, achieving multi-timescale coordination for optimal energy allocation from seconds to years; second, handling complex constraints to ensure safe and stable system operation; third, balancing economy and reliability, seeking the optimal solution between minimum cost and minimum risk. However, existing algorithms face significant limitations: meta-heuristic algorithms like standard PSO are prone to falling into local optima in high-dimensional decision spaces, making it difficult to handle the multi-scenario, multi-objective optimization problems of hydrogen-integrated energy systems; traditional mathematical programming methods have low solving efficiency for nonlinear, non-convex problems and struggle to address uncertainties; the computational complexity of mixed-integer programming methods increases exponentially with problem scale, making it difficult to meet engineering real-time requirements. These limitations constrain the optimal dispatch capability of energy storage systems in complex energy environments, urgently necessitating the development of new intelligent optimization algorithms.

## 3. Modeling of Hydrogen Energy Storage Power System

### 3.1. Overall System Architecture

With the increasing share of installed capacity of renewable energy sources like wind and solar, the contradiction of seasonal electricity imbalance in the power system becomes prominent, threatening the power supply reliability of the system.

### 3.2. Key Component Models

The hydrogen production component model serves as a bridge connecting upper-level optimal dispatch commands with underlying physical devices. Its core role is to convert

the power purchase/dispatch commands from the scheduling algorithm into predictable hydrogen production, power consumption, heat generation, and operating states, while ensuring these operations strictly adhere to the safety and performance boundaries of the equipment.

Electrolyzer modeling requires following a multi-level strategy of "mechanism-component-system":

**Electrochemical Mechanism Level:** Based on electrochemical kinetics and thermodynamics, describing the voltage-current characteristics and energy distribution of a single electrolyzer cell.

**Component-System Level:** Integrating the stack, power conversion, gas processing, and thermal management subsystems to form the steady-state and dynamic input (electrical energy)-output (hydrogen, heat, oxygen) characteristics of the complete unit.

**Optimal Control Level:** Abstracted as decision variables subject to multiple constraints in the system dispatch model. Its operating state directly affects the system's power balance, economic cost, and carbon emission reduction goals.

The operating voltage  $V_{cell}$  of a single electrolyzer cell is the sum of the reversible voltage and various overpotentials, determining the theoretical limit and practical losses of energy conversion.

$$V_{cell} = E_{rev} + \eta_{act,a} + |\eta_{act,c}| + \eta_{ohm} + \eta_{diff} \quad (1)$$

In the formula,  $E_{rev}$  is the reversible decomposition voltage, determined by the Gibbs free energy change of the reaction:

$$E_{rev} = \frac{\Delta G}{2F} + \frac{RT}{2F} \ln \left( \frac{P_{H_2} P_{O_2}^{\frac{1}{2}}}{a_{H_2O}} \right) \quad (2)$$

In the formula,  $\Delta G$  is the standard Gibbs free energy change, which slightly decreases as temperature increases.  $F$  is the Faraday constant.  $P_{H_2}$ ,  $P_{O_2}$  are the partial pressures of hydrogen and oxygen, respectively.  $a_{H_2O}$  is the activity of water.

The activation overpotential  $\eta_{act}$  is the additional voltage required to drive the electrochemical reactions at the cathode and anode, conforming to the Butler-Volmer equation, often simplified by the Tafel formula:

$$\eta_{act} = \frac{RT}{\alpha n F} \ln \left( \frac{j}{j_0} \right) \quad (3)$$

In the formula,  $j$  is the current density,  $j_0$  is the exchange current density,  $\alpha$  is the charge transfer coefficient.

The ohmic overpotential  $\eta_{ohm}$  is caused by the resistance of ions passing through the membrane and electrons passing through the electrode materials:

$$\eta_{ohm} = j \cdot ASR_{ohm}(T, \lambda) \quad (4)$$

In the formula,  $ASR_{ohm}$  is the area-specific resistance.

Summing the above voltage components yields the polarization curve describing the relationship between input voltage and current density. The voltage efficiency of the electrolyzer is defined as:

$$\eta_V = \frac{E_{rev}}{V_{cell}} \quad (5)$$

Typically,  $\eta_V$  can reach 60-75% near the rated power. The current efficiency  $\eta_F$  represents the proportion of current used for the main reaction, usually greater than 95%. The overall electrical-to-hydrogen conversion efficiency is:

$$\eta_{elec} = \eta_V \cdot \eta_F = \frac{\dot{m}_{H_2} \cdot HHV_{H_2}}{P_{DC,in}} \quad (6)$$

Where  $HHV_{H_2}$  is the higher heating value of hydrogen.

In system optimization, semi-empirical models based on polarization curves and energy balances are often used.

The core relationship between the DC input power of the electrolyzer and hydrogen production rate is:

$$P_{DC,in} = N_{cell} \cdot A \cdot j \cdot V_{cell}(j, T, p) \quad (7)$$

$$\dot{m}_{H_2} = \eta_F(j, T) \cdot \frac{N_{cell} \cdot A \cdot j}{2F} \cdot M_{H_2} \quad (8)$$

In the formula,  $N_{cell}$  is the number of cells connected in series in the stack,  $A$  is the effective area,  $p$  is a vector of operating parameters like pressure.

Considering AC power supply and auxiliary power consumption, the system efficiency from the AC side to hydrogen is:

$$\eta_{sys} = \frac{\dot{m}_{H_2} \cdot HHV_{H_2}}{P_{AC,in}} = \eta_{elec} \cdot \eta_{AC/DC} \cdot (1 - \alpha_{aux}) \quad (9)$$

Where  $\alpha_{aux}$  is the proportion of auxiliary system power consumption.

During electrolysis, most of the electrical energy not converted to hydrogen chemical energy is released as heat:

$$Q_{gen} = P_{DC,in} - \dot{m}_{H_2} \cdot \Delta H \quad (10)$$

Where  $\Delta H$  is the enthalpy change of the water-splitting reaction. This heat must be removed by the cooling system to maintain the stack at 60-80°C. The usable low-temperature waste heat  $Q_{waste}$  is:

$$Q_{waste} = \varepsilon_{HR} \cdot (Q_{gen} - Q_{cool,loss}) \quad (11)$$

In optimization, this heat can be considered for integration into the system's thermal network.

The electrolyzer system efficiency  $\eta_{sys}$  is a function of the load factor, exhibiting nonlinearity. Typically, within the 20%-100% rated power range, efficiency first increases then decreases, with an optimal efficiency point. Optimal dispatch should avoid prolonged operation in the low-load region.

Electrical dynamics: Power electronics response is fast, generally at the millisecond level, and can be approximated as instantaneous.

## 4. Loss Function Design

### 4.1. Multi-Objective Loss Function

The optimization framework employs a composite loss function, balancing different image quality requirements, formulated as Equation (12):

$$L_G = \lambda_{adv} \cdot L_{adv} + \lambda_{recon} \cdot L_{recon} + \lambda_{cycle} \cdot L_{cycle} \quad (12)$$

The adversarial loss ( $L_{adv}$ ) reduces deep feature distribution differences and is defined as Equation (13):

$$L_{adv} = -E_{I_{LR} \sim p_{data}} [\log D(G(I_{LR}))] \quad (13)$$

The reconstruction loss ( $L_{recon}$ ) uses the  $L_1$  norm for pixel-level numerical accuracy, which is robust against outliers and crucial for preserving identity semantics, defined as Equation (14):

$$L_{recon} = E_{I_{LR}, I_{HR} \sim p_{data}} [\|G(I_{LR}) - I_{HR}\|_1] \quad (14)$$

## 4.2. Cycle Consistency Loss

This self-supervised constraint is a key innovation, forming a "reconstruction-degradation" closed loop. The reconstructed image  $I_{SR}$  is re-degraded using the estimated kernel  $M_{est}$ , as Equation (15):

$$I_{cycle} = D(I_{SR}, M_{est}) \quad (15)$$

The consistency loss calculates the difference between this re-degraded image and the original input  $I_{LR}$ , as Equation (16) and simplified as Equation (17):

$$L_{cycle} = E_{I_{LR} \sim p_{data}} [\| D(G(I_{LR}), M_{est}) - I_{LR} \|_1] \quad (16)$$

$$L_{cycle} = \| D(G(I_{LR})) - I_{LR} \|_1 \quad (17)$$

This forces the network to learn a physically meaningful and reversible degradation model.

## 5. Conclusion

Optimized with cycle consistency constraints, a multi-scale discriminator, and a progressive two-stage training strategy, FiBSR provides a robust and systematic solution that outperforms existing mainstream methods in both subjective and objective evaluations, laying a solid foundation for practical applications in complex degradation scenarios.

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