

Write a comprehensive, detailed summary with beautiful formatting.with all formulas

Certainly! Below is a comprehensive and detailed summary of the key topics and methodologies covered in the document, including relevant formulas, organized neatly for clarity and readability.

Intelligent Data Analytics for Power and Energy Systems: A Comprehensive Summary

This summary encapsulates the state-of-the-art research and intelligent methodologies applied to power and energy systems, focusing on advanced data analytics, control schemes, optimization techniques, renewable energy integration, and system stability. The compilation draws from a wide array of contributions addressing cyber-physical systems, distributed generation, renewable energy forecasting, and intelligent control.

1. Intelligent Analysis and Diagnosis in Power Systems

1.1 SCADA Systems Attack and Fault Diagnosis

Supervisory Control And Data Acquisition (SCADA) systems automate power station processes but lack the capability to distinguish between faults, cyber-attacks, and maintenance events. Machine learning classifiers are developed to identify and classify these malfunctions efficiently.

- **Fault Current Calculation for Unsymmetrical Faults:**

$$I_f = I_0 + \alpha I_1 + \alpha^2 I_2$$

where

$$I_0, I_1, I_2$$

are zero, positive, and negative sequence components, and

$$\alpha = 1\angle 120^\circ$$

- **Fault Current Categorization:**

Category	Current Magnitude (A)
Zero	0–50

Category	Current Magnitude (A)
Normal	50–200
Warning	200–400
High	>400

- **Classification Rules Based on Relay Logs and Fault Current:**

Using relay control logs (control log, snort log, relay log), fault current magnitude, and switching statuses, the system states are classified into **No-event, Fault, Attack** with high accuracy (~97%) [[24]-[47]].

2. Distributed Generation Planning and Network Reconfiguration

2.1 Multi-objective Optimization with Adaptive Particle Swarm Optimization (APSO)

- **Objective Function (Multi-objective):**

$$\text{Fitness} = \eta_1 I_{PL} + \eta_2 I_{VD} + \eta_3 I_{QL} + \eta_4 I_R$$

where:

—

$$I_{PL}$$

: Active power loss index

—

$$I_{VD}$$

: Voltage deviation index

—

$$I_{QL}$$

: Reactive power loss index

—

$$I_R$$

: Reliability index (sum of SAIFI, SAIDI, CAIDI, AENS)

– Weight factors

$$\eta_1 = 0.40, \eta_2 = 0.20, \eta_3 = 0.25, \eta_4 = 0.15$$

- **Backward–Forward Sweep Load Flow:**

Load current at iteration

$$k$$

:

$$LC(t)^k = \frac{(P_L(t) + jQ_L(t))}{V^{k-1}(t)}$$

Branch current via Bus Injection to Branch Current (BIBC) matrix:

$$[BC] = [BIBC][LC]$$

Voltage update:

$$V_i = V_j - BC_{(j-1)} \times Z_{ji}$$

- **APSO Velocity and Position Update:**

$$v(k+1) = \xi [w(k) \cdot v(k) + c_1 \cdot rand \cdot (Y_{locbest}(k) - Y(k)) + c_2 \cdot rand \cdot (Y_{gbest}(k) - Y(k))]$$

$$Y(k+1) = Y(k) + v(k+1)$$

with inertia weight:

$$w = w_{max} - \frac{(w_{max} - w_{min}) \cdot \text{Itr}}{\text{Itr}_{max}}$$

and constriction factor:

$$\xi = \frac{2}{|2 - \psi - \sqrt{\psi^2 - 4\psi}|}, \quad \psi = c_1 + c_2 = 4.1$$

2.2 Results and Observations

- Configurations combining DGs and network reconfiguration reduce power losses significantly and improve voltage profiles and reliability (up to ~98.97%) [[52]-[66]].

3. Direct Torque Control-Space Vector Modulation (DTC-SVM) of Doubly Fed Induction Generator (DFIG)

- Voltage Equations (d-q axis):

$$V_{sd} = R_s I_{sd} - \omega_s \psi_{sq} + \frac{d\psi_{sd}}{dt}$$

$$V_{sq} = R_s I_{sq} + \omega_s \psi_{sd} + \frac{d\psi_{sq}}{dt}$$

$$V_{rd} = R_r I_{rd} - \omega_r \psi_{rq} + \frac{d\psi_{rd}}{dt}$$

$$V_{rq} = R_r I_{rq} + \omega_r \psi_{rd} + \frac{d\psi_{rq}}{dt}$$

- Flux Linkages:

$$\psi_{sd} = L_m I_{rd} + L_s I_{sd}$$

$$\psi_{rd} = L_m I_{sd} + L_r I_{rd}$$

$$\psi_{sq} = L_m I_{rq} + L_s I_{sq}$$

$$\psi_{rq} = L_m I_{sq} + L_r I_{rq}$$

- Electromagnetic Torque:

$$T_e = -\frac{3}{2} p \frac{L_m}{L_s} (\psi_{sd} I_{rq} - \psi_{sq} I_{rd})$$

- Space Vector Modulation (SVM):

Generation of reference voltage vectors by combining basic vectors, maintaining constant switching frequency and reducing torque/flux ripples.

- Results:

Fast dynamic response and good steady-state performance verified by MATLAB/Simulink simulations [[68]-[84]].

4. Load Frequency Control (LFC) in Deregulated Power Systems

4.1 System Model

- Two-area non-reheat thermal system with Disco participation matrix (DPM) for Genco-Disco power exchanges.
- **State-space Model:**

$$\dot{x} = Ax + Bu + FP_L + \Gamma P_{UC}$$

- **Area Control Error (ACE):**

$$ACE_i = B_i \Delta f_i + \Delta P_{tie_i}$$

4.2 Controllers Studied

- **Model Predictive Control (MPC)**
- **Proportional Integral Derivative (PID)**
- **Linear Quadratic Gaussian (LQG)**
- **Fuzzy Cascaded PID**
- **PID Controller Transfer Function:**

$$G_{PID}(s) = K_P + \frac{K_I}{s} + K_D s$$

- PID gains optimized using Big Bang Big Crunch (BBBC) algorithm.

4.3 Performance Metrics

- Frequency deviation, tie-line power deviations, overshoot, undershoot, settling time.
- **Results:**

MPC outperforms others in settling time and robustness; fuzzy cascaded PID and LQG also show competitive results [[85]-[104]].

5. Short-Term Hydro Scheduling (STHS): Mathematical Approaches

5.1 Objective Functions

- Revenue Maximization:

$$\max f_1 = \sum_{t \in T} M_p^t \cdot \Delta T \cdot P_{sl}^t$$

- Operational Cost Minimization:

$$\min f_2 = \sum_{t \in T} \sum_{h \in H} \sum_{i \in I_h} S U_{i,h} \cdot \mu_{i,h,t}$$

- Energy Utilization Optimization:

$$\min f_{3a} = \sum_{r \in R} W_{mf_{r,t}} \cdot E_h \cdot (V_{in_{r,0}} - v_{r,t})$$

$$\max f_{3b} = \sum_{r \in R} W_{mf_{r,t}} \cdot E_h \cdot v_{r,t}$$

5.2 Problem Type

- Unit-based STHS models for cascaded hydropower plants, addressing start-up/shutdown costs, head variation, and efficiency losses.

5.3 Solution Techniques

- Linear/Nonlinear programming, Mixed Integer Linear Programming (MILP), Dynamic Programming (DP), Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and other metaheuristics [[105]-[119]].
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6. Power System Stability Analysis Using UPFC

- Voltage Stability Index (L-Index):

$$L_j = \left| 1 - \sum_{i \in \alpha_G} F_{ji} \frac{V_i}{V_j} \right|$$

where

$$V_i, V_j$$

are bus voltages,

$$F_{ji}$$

are elements from system matrices.

- **Unified Power Flow Controller (UPFC):**

Combines series and shunt compensators for flexible voltage and power flow control.

- Load flow equations modified to include UPFC power injections

$$P_s, Q_s$$

:

$$P_{G_l} - P_{D_l} - \sum_{m=1}^{N_{ac}} V_l V_m (G_{lm} \cos \delta_{lm} + B_{lm} \sin \delta_{lm}) - P_{s_l} = 0$$

$$Q_{G_l} - Q_{D_l} - \sum_{m=1}^{N_{ac}} V_l V_m (G_{lm} \sin \delta_{lm} - B_{lm} \cos \delta_{lm}) - Q_{s_l} = 0$$

- **Results:**

UPFC placement between the most sensitive buses (identified by highest L-index) improves voltage profiles and system stability significantly [[120]-[134]].

7. P-Q Control Technique for Grid-Connected Solar Photovoltaic (SPV) Plants

- **Control Strategy:**

- MPPT using Perturb and Observe (P&O) algorithm to track maximum power.
- Grid side voltage transformed from abc to

$$\alpha\beta$$

- , then to d-q frame using Phase-Locked Loop (PLL).
- Decoupled active and reactive current components

$$I_d, I_q$$

controlled via PI controllers.

- **Active and Reactive Power Calculation:**

$$P = 1.5(V_d I_d + V_q I_q)$$

$$Q = 1.5(V_q I_d - V_d I_q)$$

- **Inverter Control:**

PWM signals generated from PI controller outputs to control inverter switches.

- **Results:**

System operates effectively under varying irradiance and temperature; active power control to grid is accurately maintained [[135]-[150]].

8. Data Analytics and Intelligent Tools for Solar Photovoltaic Systems

- **Software Tools:**

- **PVGIS:** Free, web-based tool for solar radiation and power generation estimation.
- **PVsyst:** Paid, comprehensive software with advanced features like module degradation, shading analysis, and loss modeling.

- **Performance Ratio (PR):**

$$PR = \frac{\text{Total Energy (Meter)}}{\text{Total Solar Irradiation} \times \text{Module Area} \times \text{Module Efficiency}} \times 100\%$$

- **Degradation Analysis:**

PVsyst can simulate annual degradation and losses, helping in predictive maintenance.

- **Case Study:**

Simulation and actual data from a 500 kW rooftop PV plant in Lucknow, India, show PVsyst providing more accurate forecasting than PVGIS [[319]-[353]].

9. AI-Based Maximum Power Point Tracking (MPPT) for Renewable Energy Systems

- Challenges with Conventional MPPT:

- Trapping at local maxima under partial shading conditions (PSC).
- Oscillations around MPP.
- Slow transient response.

- AI-Based MPPT Techniques:

- **Fuzzy Logic Controller (FLC)**
- **Artificial Neural Networks (ANN)**
- **Genetic Algorithm (GA)**
- **Swarm Intelligence (SI):** Particle Swarm Optimization (PSO), Cuckoo Search (CS), Firefly Algorithm (FA), etc.
- **Hybrid Algorithms:** Combines AI and heuristic methods for better performance.
- **Machine Learning (ML):** Bayesian ML, Extreme Learning Machines (ELM), Reinforcement Learning (RL).

- FLC Rules:

For error

$$E$$

and change in error

$$\Delta E$$

:

- If

$$E > 0$$

and

$$\Delta E > 0$$

then decrease duty cycle

$$D$$

- If

$$E > 0$$

and

$$\Delta E < 0$$

then increase

$$D$$

- If $E < 0$
and $\Delta E > 0$
then increase D
- If $E < 0$
and $\Delta E < 0$
then decrease D

- **AI MPPT Comparison Highlights:**

Technique	Tracking Accuracy	Speed	Complexity	PSC Handling	Cost
FLC	Moderate	Moderate	Moderate	Poor	Moderate
ANN	High	Fast	High	Poor	High
SI	High	Fast	Moderate	High	Moderate
Hybrid	High	Fast	High	High	High
GA	Moderate	Moderate	High	High	Moderate
ML	High	Moderate	High	Slight	High

- **Simulation Results:**

AI-based MPPT algorithms outperform conventional methods under PSC with reduced oscillations and faster convergence [[373]-[416]].

10. Intelligent Modeling for PV Parameter Estimation and Fault Diagnosis

- **PV One-Diode Model (ODM):**

$$I_L = I_{ph} - I_d - \frac{V_L + I_L R_s}{R_{sh}}$$

$$I_d = I_0 \left[\exp \left(\frac{V_L + I_L R_s}{\eta V_t} \right) - 1 \right]$$

where:

- I_{ph}
- : Photo-generated current,
- I_0
- : Reverse saturation current,
- R_s, R_{sh}
- : Series and shunt resistances,
- η
- : Ideality factor,
- V_t
- : Thermal voltage.

- **Parameter Estimation using Extreme Learning Machine (ELM) and Feedforward Neural Network (FNN) with Levenberg–Marquardt Algorithm:**

Models trained on experimental data of solar irradiance, temperature, and electrical parameters.

- **Performance Metrics:**

Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Bias Error (MBE), Coefficient of Determination

$$R^2$$

:

$$MAE = \frac{1}{N} \sum_{i=1}^N |PV_i^{est} - PV_i^{meas}|$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (PV_i^{est} - PV_i^{meas})^2}$$

$$MBE = \frac{1}{N} \sum_{i=1}^N (PV_i^{est} - PV_i^{meas})$$

$$R^2 = 1 - \frac{(RMSE)^2}{\text{var}(PV_i^{est})}$$

- **Results:**

ELM and FNN models effectively estimate PV parameters with low errors, enhancing condition monitoring and fault diagnosis [[429]-[453]].

11. Transformerless Inverter System for Renewable Energy

- **Two-Stage Single-Phase System:**

- **Stage 1:** Closed-loop DC-DC Boost Converter controls DC output voltage.
- **Stage 2:** Full-bridge inverter converts DC to 50 Hz, 245 Vrms AC.

- **Design Parameters:**

- Boost converter inductance

$$L = 5 \text{ mH}$$

- Output capacitor

$$C = 5000\mu F$$

- Switching frequency

$$f_{sw} = 10 \text{ kHz}$$

- Load tested: resistive load of 33.33 Ω.

- **Simulation Results:**

- Voltage and current waveforms show stable operation.
 - Filtered inverter output approximates sinusoidal waveform.
 - System suitable for standalone household applications (~2 kW) [[451]-[480]].
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12. Performance Investigation of Direct-Drive Generator-Based Wind Energy Conversion System

- **Wind Turbine Mechanical Power:**

$$P_T = \frac{1}{2}\rho A C_p(\lambda, \beta) V_w^3$$

- **Tip Speed Ratio:**

$$\lambda = \frac{\omega_T R}{V_w}$$

- **Drive Train Dynamics:**

$$\frac{d\omega_\tau}{dt} = \frac{1}{J_\tau} [T_\tau - (K_s \delta\theta + B\delta\omega)]$$

$$\frac{d\delta\theta}{dt} = \delta\omega$$

$$\frac{d\omega_g}{dt} = \frac{1}{J_g} \left[\frac{1}{\eta_{gear}} (K_s \delta\theta + B\delta\omega) - T_e \right]$$

- **PMSG Electrical Model (d-q frame):**

$$\frac{di_{sd}}{dt} = -\frac{R_a}{L_d} i_{sd} + \omega \frac{L_q}{L_d} i_{sq} + \frac{1}{L_d} u_d$$

$$\frac{di_{sq}}{dt} = -\frac{R_a}{L_q} i_{sq} - \omega \left(\frac{L_d}{L_q} i_{sd} + \frac{\psi_m}{L_q} \right) + \frac{1}{L_q} u_q$$

- **Results:**

MPPT control using Tip Speed Control (TSC), Artificial Intelligence (ANN, GA, PSO) efficiently extracts maximum power under variable wind speeds [[471]-[494]].

13. Fuel-Constrained Economic Emission Dispatch Optimization

- **Objective Functions:**

- **Fuel Cost:**

$$F_c = \sum_{m=1}^M \sum_{i=1}^N t_m \left[a_i + b_i P_{im} + c_i P_{im}^2 + |d_i \sin(e_i (P_{min_i} - P_{im}))| \right]$$

- **Emission Level:**

$$F_e = \sum_{m=1}^M \sum_{i=1}^N t_m [\alpha_i + \beta_i P_{im} + \gamma_i P_{im}^2 + \sigma_i \exp(\theta_i P_{im})]$$

- **Constraints:**

- Power balance:

$$\sum_{i=1}^N P_{im} = P_{D_m}$$

- Fuel delivery and storage:

$$V_{im} = V_i(m-1) + F_{im} - t_m(\eta_i + \delta_i P_{im} + \mu_i P_{im}^2)$$

- **Solution Method:**

Multi-objective Differential Evolution (MODE) algorithm used to optimize fuel cost and emission simultaneously, compared against Strength Pareto Evolutionary Algorithm 2 (SPEA2) [[131]-[158]].

14. Adaptive Critic Scheme for Multi-area Automatic Generation Control (AGC)

- **System Dynamics:**

$$\dot{x} = Ax + Bu$$

- **Cost Function:**

$$J = \frac{1}{2} \int_0^\infty (x^T Q x + u^T R u) dt$$

- **Policy Iteration (PI) Control Update:**

- Policy Evaluation:

$$x_t^T P_i x_t = \int_t^{t+T} x_\tau^T (Q + K_i^T R K_i) x_\tau d\tau + x_{t+T}^T P_i x_{t+T}$$

- Policy Improvement:

$$K_{i+1} = R^{-1} B^T P_i$$

- **Results:**

PI-based adaptive control outperforms classical LQR in transient response and robustness, meeting NERC CPS1 and CPS2 standards [[159]-[183]].

15. VSC-HVDC Converter Installation Using Metaheuristic Optimization

- **Unified Optimal Power Flow (OPF) Model:**

Modified power flow equations incorporating active/reactive power injections

$$P_s, Q_s$$

at Point of Common Coupling (PCC):

$$P_{G_l} - P_{D_l} - \sum_{m=1}^{N_{ac}} V_l V_m (G_{lm} \cos \delta_{lm} + B_{lm} \sin \delta_{lm}) - P_{s_l} = 0$$

$$Q_{G_l} - Q_{D_l} - \sum_{m=1}^{N_{ac}} V_l V_m (G_{lm} \sin \delta_{lm} - B_{lm} \cos \delta_{lm}) - Q_{s_l} = 0$$

- **Objective Functions:**

- Minimize Average Line Loadability:

$$S_{avg} = \frac{1}{nl} \sum_{j=1}^{nl} \frac{S_j}{S_{jmax}}$$

- Minimize Voltage Stability Index (L-index):

$$f_2 = \min \max_i (L_i)$$

- **Optimization Algorithm:**

Particle Swarm Optimization (PSO) applied to solve unified OPF for hybrid AC-DC system.

- **Results:**

Optimal placement of VSC-HVDC converter improves voltage stability and reduces congestion compared to AC-only systems [[185]-[224]].

16. Comprehensive Data Analytics of Microgrid Applications

- **Microgrid Control Modes:**
 - Centralized Control: Single controller manages entire microgrid.
 - Decentralized Control: Individual controllers for distributed units.
 - P-Q Control: Inverters regulated to supply specified active/reactive power.
 - Droop Control: Mimics governor behavior to share load among parallel inverters.
- **Microgrid Status in India:**
 - Rapid growth driven by renewable energy integration.
 - Challenges include scalability, cost, and technical complexity.
 - Major projects include solar-based microgrids and biomass initiatives [[517]-[545]].
- **Data Analytics Role:**

Huge volumes of data from smart meters, sensors, and DERs require intelligent analytics for optimization, forecasting, and control [[529]-[545]].

17. Security Challenges in IoT-Integrated Power and Energy Systems

- **Key Issues:**
 - Data privacy and integrity.
 - Resource constraints in IoT devices.
 - Scalability and lightweight cryptographic mechanisms.
- **Blockchain Integration:**
 - Provides tamper-proof, decentralized data storage.
 - Enhances security and privacy in healthcare and energy management.
 - Challenges remain in designing efficient consensus and smart contract systems [[537]-[562]].

18. Nature-Inspired Optimization Techniques: Comparative Analysis

- **Algorithms Compared:**
 - Social Group Optimization (SGO)
 - Particle Swarm Optimization (PSO)

- Simulated Annealing (SA)
- Genetic Algorithm (GA)
- Cuckoo Search (CS)
- Artificial Bee Colony (ABC)
- Farmland Fertility Optimization
- Firefly Optimization (FO)
- Water Cycle Optimization (WCO)
- Teaching–Learning-Based Optimization (TLBO)
- Antlion Optimization (ALO)

- **Test Function:**

Sphere function minimized over 2 variables:

$$f(x) = x_1^2 + x_2^2$$

- **Convergence Order (Best to Worst):**

GA > Farmland Fertility > TLBO > PSO > ALO > SA > ABC > CS > FO > SGO > WCO

- **Implementation:**

MATLAB codes provided, with convergence plots and comparative tables [[591]-[617]].

Conclusion

This comprehensive overview highlights the critical role of intelligent data analytics, advanced control methodologies, and nature-inspired optimization algorithms in modern power and energy systems. From cyber-attack detection in SCADA, distributed generation planning, renewable energy forecasting, to microgrid control and security, these techniques enable efficient, reliable, and sustainable energy management.

The interplay of machine learning, evolutionary algorithms, and novel control strategies addresses the complexity and uncertainties in power systems, ensuring optimized operation, enhanced stability, and integration of renewable resources.

The MATLAB implementations of various optimization algorithms underscore practical applicability and comparative efficiency in solving complex nonlinear problems.

References

For detailed references, please consult the original document pages [[1]] to [[617]].

This summary integrates formulas and findings from multiple chapters to provide a unified understanding of intelligent data analytics applications in power and energy systems.
