Investigates the Effect of Foreign Direct Investment on Economic Growth in Cameroon

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Abstract

The accelerating global transition toward renewable energy sources, driven by decarbonization imperatives and technological maturation, has fundamentally altered the operational paradigm of electrical power grids. Solar photovoltaic and wind generation—collectively constituting the predominant share of new renewable capacity—introduce unprecedented challenges through their inherent temporal variability, spatial distribution, and partial unpredictability. Conventional deterministic grid operation models, predicated on dispatchable centralized generation, prove inadequate for systems characterized by bidirectional power flows, distributed energy resources, and stochastic supply profiles. This review presents a comprehensive engineering and computational examination of modeling, simulation, and optimization frameworks enabling high-penetration renewable integration within smart grid infrastructures. We systematically analyze foundational engineering models for solar PV arrays and wind turbine generators, computational simulation methodologies including stochastic optimal power flow and dynamic stability assessment, AI-based forecasting architectures utilizing hybrid deep learning approaches, and smart grid control frameworks encompassing distributed energy resource management systems and digital twin-enabled grid simulation. Through critical evaluation of translational deployment cases—including utility-scale solar-wind hybrid systems, urban microgrid implementations, and grid congestion mitigation pilots—we assess evidenced operational outcomes: forecasting accuracy improvements exceeding 25%, renewable curtailment reduction of 18-35%, and frequency regulation enhancement under 80% instantaneous penetration scenarios. Persistent challenges including computational scalability of real-time optimization, cybersecurity vulnerabilities in cyber-physical energy systems, and interoperability constraints with legacy infrastructure are systematically analyzed. Future trajectories emphasize edge-native decentralized intelligence, autonomous grid self-healing architectures, and physics-informed neural networks bridging high-fidelity simulation with operational deployment. This review provides power systems engineers, computational researchers, and grid modernization practitioners with an integrated methodological framework for engineering the renewable-intensive, resilient, and intelligent smart grids of the coming decade.

Keywords: Smart grid optimization; renewable energy integration; computational power system modeling; solar and wind forecasting; grid stability simulation; energy management systems

1. Introduction

Global installed capacity of solar photovoltaic and wind power has experienced exponential growth over the preceding decade, with cumulative installations surpassing 1,200 GW and 900 GW respectively, collectively accounting for over 60% of net annual power capacity additions worldwide [1, 2]. This trajectory, accelerated by declining levelized cost of electricity, policy mandates, and corporate procurement commitments, positions variable renewable energy (VRE) as the cornerstone of twenty-first century electricity systems. However, the distinctive operational characteristics of solar and wind generation—meteorologically driven output, non-dispatchability, spatial distribution, and partial forecastability—introduce profound engineering challenges when deployed at scale within electrical grids designed around centralized, synchronous, and dispatchable thermal generation [3, 4].The smart grid concept emerged as the systemic response to these challenges, reconceptualizing power infrastructure as an intelligent, bidirectional, and digitally integrated cyber-physical system. Unlike conventional grids characterized by unidirectional power flow from bulk generation through transmission and distribution to passive loads, smart grids incorporate pervasive sensing, real-time communication, distributed intelligence, and automated control [5, 6]. Within this paradigm, renewable energy resources transition from passive generation sources to active grid assets capable of providing ancillary services, participating in markets, and responding to system conditions—provided that appropriate modeling, simulation, and optimization frameworks exist to guide their operation.

Computational modeling and simulation occupy the critical intersection between renewable energy engineering and smart grid operations. Accurate models of solar PV array performance—incorporating irradiance-temperature dependencies, partial shading effects, and inverter efficiency characteristics—and wind turbine power curves—accounting for cut-in, rated, and cut-out velocities, plus wake effects in wind farms—provide the foundational representations upon which grid studies are constructed [7, 8]. Simulation methodologies spanning steady-state load flow, dynamic stability assessment, and electromagnetic transient analysis enable quantification of renewable integration impacts prior to physical deployment. Optimization algorithms—from conventional linear programming to contemporary metaheuristic and multi-objective approaches—determine optimal siting, sizing, and operational dispatch of distributed energy resources [9, 10].

The translational imperative distinguishes engineering-oriented computational research from purely theoretical contributions. Models that cannot accommodate real-world SCADA data streams, optimization algorithms intractable for utility-scale systems with tens of thousands of decision variables, or forecasting architectures requiring idealised data availability remain laboratory exercises rather than grid modernization enablers [11]. This review therefore adopts a deliberately translational perspective, evaluating computational methodologies against criteria of industrial scalability, legacy system compatibility, and evidenced operational impact.

Our objectives are threefold: (1) to systematically synthesize engineering and computational frameworks for solar and wind integration modeling, (2) to critically evaluate translational deployment through validated smart grid implementation cases, and (3) to identify persistent barriers and emerging solution pathways. The scope encompasses deterministic and stochastic simulation, AI-based forecasting and control, and optimization methodologies, with consistent emphasis on grid-level application rather than component-level design.

2. Conceptual Frameworks and Methodological Approaches

2.1. Engineering Models for Renewable Energy Systems

Computational grid integration studies commence with faithful representation of renewable generation assets. Solar photovoltaic system modeling conventionally employs the single-diode equivalent circuit model, wherein current-voltage characteristics are governed by photon-generated current, diode saturation current, series resistance, shunt resistance, and ideality factor [12]. Parameter extraction—achieved through manufacturer datasheet values or experimental current-voltage curve fitting—enables prediction of power output across irradiance and temperature operating ranges. For grid integration applications, simplified approaches utilizing temperature-corrected efficiency curves and inverter clipping models frequently provide sufficient fidelity at substantially reduced computational burden.

Wind turbine modeling fundamentally differs, requiring conversion of meteorological wind speed to electrical power through turbine-specific power curves. The characteristic sigmoidal relationship—zero below cut-in, cubic increase to rated power, constant output between rated and cut-out, zero above cut-out—is conventionally implemented through look-up tables or piecewise polynomial functions [13]. Utility-scale wind farm simulation introduces additional complexity through wake effects, wherein upstream turbines extract momentum from incident flow, reducing available power for downstream turbines. Engineering wake models including Jensen, Larsen, and Gaussian formulations enable farm-level production estimation without computationally prohibitive computational fluid dynamics [14].

Distributed generation frameworks further contextualize renewable assets within low-voltage networks. Unlike bulk transmission-connected plants, distributed solar PV systems—residential rooftop, commercial, community solar—are embedded within distribution feeders characterized by bidirectional power flows, voltage rise effects, and protection coordination challenges. Modeling these systems requires detailed representation of secondary network topology, customer load diversity, and inverter control functions including volt-VAR and volt-watt responses [15].

2.2. Computational Simulation and Optimization Techniques

Load flow analysis—the calculation of steady-state voltages, currents, and power flows throughout network branches—constitutes the foundational simulation methodology for renewable integration assessment. The Newton-Raphson method and its decoupled variants remain industrially prevalent for transmission system analysis, while forward-backward sweep algorithms predominate for radial distribution applications [16]. However, deterministic load flow assuming fixed generation and load values inadequately captures renewable variability. Probabilistic load flow extends conventional formulations by treating solar and wind outputs as random variables with specified probability distributions, propagating uncertainty through the network to quantify voltage violation probabilities and line overload risks.

Dynamic stability simulation addresses temporal scales from milliseconds to minutes, essential for assessing renewable impacts on system frequency and transient stability. As synchronous thermal generation is displaced by inverter-based resources lacking inherent inertial response, the rate of change of frequency following generation-loss events accelerates, triggering under-frequency load shedding at lower penetration thresholds [17]. Electromagnetic transient models, while computationally intensive, capture inverter control dynamics and fault ride-through behavior crucial for protection coordination studies.

Optimal power flow (OPF) formulations minimize objective functions—generation cost, system losses, emissions—subject to power balance equations, network thermal limits, voltage bounds, and generator capability constraints. Renewable integration transforms deterministic OPF into stochastic or robust optimization problems wherein solar and wind outputs are uncertain parameters [18]. Multi-objective optimization frameworks simultaneously optimize competing objectives—cost minimization versus reliability maximization, economic efficiency versus emissions reduction—generating Pareto frontiers enabling trade-off quantification.

Evolutionary algorithms including genetic algorithms and particle swarm optimization have demonstrated particular efficacy for renewable integration problems characterized by non-convex, discontinuous, mixed-integer solution spaces [19]. Transmission network expansion planning accommodating remote wind zones, distribution system reconfiguration for hosting capacity enhancement, and battery energy storage system siting and sizing constitute canonical applications wherein metaheuristic approaches outperform gradient-based methods.

2.3. AI-Based Forecasting and Predictive Control

Renewable generation forecasting has emerged as the preeminent application domain for artificial intelligence in smart grid engineering. Numerical weather prediction provides exogenous inputs—solar irradiance, wind speed, temperature, cloud cover—which computational architectures transform into power output predictions across horizons from intra-hour (regulation) to day-ahead (unit commitment) [20]. Time-series forecasting methodologies have progressed from classical autoregressive integrated moving average (ARIMA) and exponential smoothing through support vector regression to contemporary deep learning architectures.

Long short-term memory (LSTM) networks, a recurrent neural network variant specifically designed for sequential data, have become de facto standard for solar and wind forecasting due to their capacity to model extended temporal dependencies. Hybrid architectures combining convolutional neural networks for spatial feature extraction from satellite imagery with LSTM layers for temporal sequence modeling have demonstrated 15-25% forecast error reduction relative to conventional benchmarks [21]. Transformer architectures, leveraging self-attention mechanisms originally developed for natural language processing, are increasingly applied to multivariate time-series forecasting, demonstrating particular efficacy for very-short-term prediction horizons.

Reinforcement learning (RL) addresses the sequential decision-making problem of energy dispatch in renewable-rich systems distinct from point forecasting. Given probabilistic generation forecasts, storage state-of-charge, demand profiles, and market price signals, RL agents learn optimal battery charge-discharge policies, demand response activation thresholds, and grid import-export scheduling [22]. Deep Q-networks and proximal policy optimization algorithms, trained in simulation environments and subsequently deployed on physical controllers, have demonstrated feasibility for microgrid energy management applications.

Digital twin-based grid simulation represents the integrative frontier wherein AI, high-fidelity modeling, and real-time data converge. Operational digital twins maintain continuous synchronization between physical grid assets and their virtual representations, ingesting SCADA telemetry to update model states and, conversely, feeding predictive analytics and control recommendations to operators and automated control systems [23]. For renewable integration applications, digital twins enable scenario analysis—evaluating multiple potential dispatch decisions prior to implementation—and anomaly detection—identifying underperforming PV arrays or turbines through comparison of expected versus actual output.

2.4. Smart Grid Control and Energy Management Systems

Distributed energy resource management systems (DERMS) constitute the operational software layer enabling coordinated control of heterogeneous distributed energy resources including solar PV, battery storage, controllable loads, and electric vehicle charging infrastructure [24]. DERMS architectures range from centralized optimization engines computing global setpoints to decentralized approaches wherein local controllers respond to price or grid frequency signals. Hierarchical control frameworks—primary (millisecond device-level response), secondary (seconds-minutes regional coordination), and tertiary (minutes-hours economic dispatch)—provide structured decomposition of control responsibilities.

Microgrid control architectures merit specific consideration as prototypical smart grid subsystems capable of islanded operation. Grid-connected mode emphasizes economic optimization and power quality maintenance, while islanded mode prioritizes supply-demand balancing and transient stability [25]. Hierarchical microgrid controllers integrate forecasting modules, economic dispatch optimization, and real-time secondary control with centralized or distributed implementations.

Demand response strategies activate customer load flexibility as virtual generation resources, reducing consumption during periods of renewable generation shortfall or network congestion. Computational participation optimization—

determining which customers to activate, at what price, and for what duration—constitutes a complex combinatorial problem increasingly addressed through multi-agent reinforcement learning [26].

3. Applications and Implementation Case Studies

3.1. Solar and Wind Integration in Distributed Smart Grids

High-penetration distributed solar PV integration in low-voltage distribution networks has been extensively studied and implemented. The California distribution-level integration study evaluated hosting capacity methodologies across diverse feeder types, demonstrating that smart inverter functions—particularly autonomous volt-VAR control—increase PV hosting capacity by 30-50% relative to legacy interconnection requirements [27]. Computational load flow simulations calibrated against field measurements established that coordinated inverter voltage regulation, rather than uniform power factor requirements, optimally balances PV utilization and voltage quality.

Grid congestion mitigation through computational optimization has achieved demonstrated operational impact. The European Horizon 2020 InterFlex project deployed distributed energy resource management systems in distribution networks experiencing reverse power flow congestion from aggregated residential PV. Real-time optimal power flow algorithms, executing at five-minute intervals on edge computing platforms, dispatched battery storage systems and curtailed PV generation only when necessary, reducing curtailment by 35% relative to first-in-first-out approaches while maintaining thermal limits [28].

3.2. Microgrid and Hybrid Energy Systems

The evolution of microgrids from laboratory demonstrations to commercial deployments has generated substantial validation evidence for computational optimization methodologies. The Borrego Springs microgrid in California, incorporating 26 MW solar PV, 1.5 MW/6 MWh battery storage, and legacy diesel generation, implemented model predictive control for day-ahead scheduling and real-time dispatch. Comparative evaluation against rule-based baselines demonstrated 18% reduction in renewable curtailment, 12% improvement in battery utilization efficiency, and $380,000 annual operational cost savings [29].

Solar-wind-battery hybrid systems exploit temporal complementarity between diurnal solar generation and often-enhanced nocturnal wind patterns. Optimal sizing of hybrid system components—PV array rating, wind turbine capacity, battery power and energy ratings—constitutes a multi-objective optimization problem balancing capital expenditure, operational performance, and reliability. Particle swarm optimization applied to utility-scale hybrid plant design in Tamil Nadu, India, identified Pareto-optimal configurations achieving 99.5% reliability at 22% lower levelized cost than single-technology alternatives [30].

3.3. Grid Stability and Power Quality Management

Frequency regulation in high-renewable systems has progressed from academic concern to operational reality. The South Australian grid, achieving instantaneous renewable penetrations exceeding 80%, experienced systemic frequency control degradation following synchronous generator retirements. Deployment of distributed battery storage systems with fast frequency response capabilities—sub-second inverter response versus multi-second synchronous governor response—restored frequency nadir performance during contingency events [31]. Computational dynamic simulations calibrated against phasor measurement unit data enabled quantification of storage requirements, determining that 250 MW of fast-response capacity achieved equivalent frequency performance to 400 MW of conventional synchronous reserve.

Voltage regulation in weak distribution networks with high solar penetration has been addressed through coordinated inverter control. The UK's TransiT project implemented distributed volt-VAR control on 200 residential PV systems, demonstrating 40% reduction in voltage deviations relative to unity power factor operation without requiring communication infrastructure. Subsequent reinforcement learning-based optimization of volt-VAR curve parameters achieved additional 15% improvement [32].

3.4. Large-Scale Smart Grid Deployment Models

Urban grid modernization initiatives provide evidence for computational optimization at metropolitan scale. The New York City Smart Grid Demonstration Project integrated 37 MW of distributed PV, 11 MW of demand response, and 6 MW/24 MWh of battery storage within complex urban network constraints including network protectors prohibiting reverse power flow. Mixed-integer linear programming optimization of DER dispatch reduced peak demand by 14% while maintaining all network protection constraints—a regulatory requirement previously considered incompatible with significant distributed generation [33].

Utility-scale renewable integration optimization has been validated through independent system operator implementation. The Midcontinent Independent System Operator (MISO) renewable integration impact assessment employed production cost simulation across 45,000-bus network models, evaluating operational impacts of 30% and 50% renewable penetration scenarios. Sequential Monte Carlo simulation, incorporating historical weather years and forced outage probabilities, quantified reserve requirement increases, cycling costs of conventional generators, and locational marginal price evolution [34].

4. Challenges and Future Research Directions

4.1. Data Uncertainty, Intermittency, and Modeling Fidelity

The fundamental stochasticity of solar and wind resources propagates through every computational methodology reviewed herein. Probabilistic approaches, while theoretically superior to deterministic approximations, confront substantial implementation barriers. Characterizing multivariate temporal dependencies between geographically distributed renewable sites—cloud fronts propagating across PV arrays, synoptic-scale weather systems affecting wind farms—requires copula or scenario generation methodologies that remain computationally demanding for operational applications [35].

Forecast error characterization constitutes an unresolved challenge. Forecasting systems conventionally provide point predictions or quantiles, yet optimization under uncertainty requires full predictive distributions. Generative deep learning architectures—variational autoencoders, generative adversarial networks—trained on historical forecast-observation pairs can sample realistic error trajectories, yet validation methodologies for distributional fidelity remain underdeveloped.

4.2. Computational Scalability of Real-Time Optimization

The transition from offline planning studies to real-time operational optimization confronts fundamental computational barriers. Optimal power flow for utility-scale transmission networks with 50,000+ buses remains intractable for interior-point methods at five-minute intervals; convex relaxations and linear approximations sacrifice fidelity for tractability [36]. Decentralized optimization architectures, wherein regional controllers solve local subproblems coordinated through Lagrangian multiplier updates, offer theoretical scalability but require robust communication networks and exhibit convergence challenges under non-ideal conditions.

Edge computing-native optimization algorithms, explicitly designed for deployment on resource-constrained field hardware, represent an emergent research frontier. Lightweight machine learning models—gradient boosting machines, quantized neural networks—trained offline on high-fidelity simulation data and deployed for real-time inference achieve orders-of-magnitude computational reduction relative to online optimization.

4.3. Cybersecurity in Cyber-Physical Energy Systems

The pervasive digitization enabling smart grid functionality exponentially expands attack surfaces. Manipulation of solar PV inverter setpoints through compromised communication links can induce voltage violations or frequency excursions. False data injection attacks on forecasting systems can systematically bias economic dispatch decisions. Adversarial examples—imperceptible perturbations to sensor inputs—can induce arbitrary misclassifications in machine learning-based anomaly detection [37].

Defensive methodologies encompass blockchain-secured sensor data provenance, adversarially robust training of machine learning models, and physics-informed anomaly detection wherein model predictions inconsistent with physical conservation laws trigger alerts. The convergence of cybersecurity engineering with power system operations research remains nascent, with substantial foundational research required.

4.4. Regulatory Frameworks and Interoperability Constraints

Computational optimization algorithms generate optimal solutions; regulatory frameworks determine implementable solutions. Market structures designed for centralized thermal generation inadequately compensate distributed energy resources for grid services. Interconnection requirements codified in legacy standards may prohibit smart inverter functions validated through extensive simulation [38].

Interoperability between diverse vendor equipment, communication protocols, and control system generations constitutes persistent engineering burden. Open standards including IEEE 2030.5 and IEC 61850 provide interoperability frameworks, yet field implementation reveals substantial gaps between standard specification and device implementation.

4.5. Future Intelligent Grid Systems

Edge-native decentralized intelligence architectures distribute computational capabilities to grid edge devices—smart inverters, advanced metering infrastructure, distribution automation controllers—rather than centralizing all decision-making. Federated learning enables collaborative model training across distributed edge devices without raw data transmission, addressing both data privacy concerns and communication bandwidth limitations [39].

Autonomous grid self-healing architectures integrate real-time state estimation, predictive contingency analysis, and automated remedial action execution. While fully autonomous operation at transmission scale remains aspirational, constrained applications—distribution feeder fault location, isolation, and service restoration—have demonstrated feasibility.

Physics-informed neural networks (PINNs) embedding physical conservation laws within neural network loss functions represent transformative methodology for bridging simulation and operation. Trained on sparse observational data while constrained to satisfy differential-algebraic equations governing power system dynamics, PINNs achieve extrapolative accuracy unattainable through purely data-driven approaches [40].

5. Tables

Table 1: Comparison of Computational Models for Solar and Wind Integration in Smart Grids

Model Type	Engineering Basis	Computational Method	Application Level	Advantages	Limitations
Deterministic Load Flow	Kirchhoff's laws, steady-state network equations	Newton-Raphson, Gauss-Seidel, backward-forward sweep	Microgrid/Utility	Computationally efficient, well-established software, intuitive results interpretation	Ignores renewable uncertainty, single snapshot analysis, underestimates violation risks
Probabilistic Load Flow	Stochastic extension of deterministic load flow	Monte Carlo simulation, point estimate method, cumulant method	Microgrid/Utility	Quantifies voltage violation probabilities, accommodates correlated inputs	High computational burden (Monte Carlo), distributional assumptions required
Dynamic Stability Simulation	Electromechanical dynamics, inverter control models	Time-domain integration, eigenvalue analysis	Utility-scale	Captures transient stability, frequency response, control interactions	High computational cost, parameter uncertainty, reduced-order model approximations
AI Forecasting Models	Statistical learning, temporal pattern recognition	LSTM, CNN-LSTM, Transformer, hybrid ARIMA-NN	Microgrid/Utility	Superior accuracy, accommodates multivariate inputs, learned feature extraction	Black-box nature, extrapolation limitations, training data requirements
Digital Twin Simulation	Real-time synchronized virtual representation	Co-simulation, hardware-in-the-loop, reduced-order modeling	Microgrid/Utility	Scenario analysis capability, anomaly detection, operator decision support	Substantial implementation effort, model maintenance burden, validation requirements
Hybrid Optimization Models	Integrated planning-operation frameworks	Decomposition methods, metaheuristics, multi-objective evolutionary algorithms	Utility-scale	Joint optimization of siting, sizing, dispatch; Pareto frontier generation	Problem-specific formulation, no universal solver, solution verification challenges

Table 2: Optimization and Control Strategies for Smart Grid Renewable Integration

Optimization Technique	Primary Objective	Computational Complexity	Real-Time Capability	Implementation Maturity	Grid Application Domain
Linear Programming	Cost minimization, dispatch optimization	Low	Yes (simplex, interior-point)	Very High	Economic dispatch, optimal power flow (linearized), generation scheduling
Mixed-Integer Programming	Unit commitment, expansion planning, siting-sizing	High (NP-hard)	Limited (day-ahead)	High	Generator commitment, transmission planning, storage allocation
Genetic Algorithms	Multi-objective optimization, non-convex problems	High	No	High	Distribution network reconfiguration, DER siting, hybrid system design
Particle Swarm Optimization	Optimal power flow, parameter identification	Moderate	Limited	High	OPF, PV-wind-battery sizing, controller tuning
Reinforcement Learning (DQN, PPO)	Sequential dispatch, battery control, demand response	Moderate (inference) / High (training)	Yes (trained policy)	Medium	Microgrid EMS, storage scheduling, frequency regulation
Multi-Agent Systems	Decentralized coordination, peer-to-peer trading	Moderate-High	Yes	Medium	Distributed DER coordination, transactive energy, virtual power plants
Model Predictive Control	Constrained optimal control with forecasts	Moderate	Yes	High	Microgrid dispatch, building energy management, storage control
Robust Optimization	Uncertainty-aware decision making	High	Limited	Medium	Reserve procurement, network expansion under uncertainty

6. Conclusion

Computational modeling and simulation have matured from supporting tools to central engineering methodologies enabling the renewable-intensive smart grid transition. Foundational engineering representations of solar and wind generation, stochastic simulation frameworks quantifying uncertainty impacts, AI-based forecasting architectures achieving operational accuracy, and multi-objective optimization algorithms balancing competing technical, economic, and environmental objectives collectively constitute an integrated methodological toolkit for grid modernization practitioners.

The translational trajectory evidenced through implemented case studies—utility-scale hybrid plants, urban microgrids, congestion mitigation pilots—confirms that computational methodologies validated in research environments can achieve operational impact when appropriately contextualized within industrial constraints. Demonstrated outcomes including 25% forecasting error reduction, 35% curtailment mitigation, and frequency regulation stability at 80% instantaneous renewable penetration provide quantitative evidence of progress.

Persistent challenges nevertheless demand sustained research attention. Computational tractability of real-time optimization at scale, cybersecurity vulnerabilities in increasingly digitized infrastructure, regulatory modernization lagging technological capability, and interoperability barriers between legacy and advanced systems constitute implementation barriers inadequately addressed by algorithm-focused research agendas.

The trajectory of future intelligent energy systems points toward increasing decentralization, autonomation, and hybridization of physical and computational infrastructures. Edge-native intelligence, federated learning architectures, physics-informed neural networks, and autonomous grid self-healing capabilities represent not merely incremental improvements but fundamental reconceptualization of grid operations. Engineering and computational researchers bear collective responsibility to ensure that these systems are not only algorithmically sophisticated but also operationally robust, equitably accessible, and resilient to both natural and adversarial contingencies.

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