Artificial Intelligence Review (2024) 57:106
https://doi.org/10.1007/s10462-024-10704-7

Artificial intelligence strategies for simulating the integrated energy systems

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Accepted: 4 January 2024 / Published online: 1 April 2024

Abstract
In recent decades, the operational impact of Artificial Intelligence (AI) strategies is massively dominating the scientific arena of improving the operation of energy systems and their hybrid integrations. Comprehensively, this paper highlights the firm methodological link of AI strategies with the different defined categories of numerical methods in hypothetically simulating the complex integrated energy systems especially the integration of Renewable Energy Sources (RES). The conducted studies in this paper are related to the bifurcations of the applied numerical simulation methodologies for efficient energy systems and the practical implementations of the optimal operated energy systems considering the integration scenarios of these methodologies with AI strategies. Furthermore, this research reviews innovatively several case studies and practical examples to emphasize the effective contributions of AI strategies in enhancing the computational analysis of numerical simulation methods forming a smart approach for assessing experimental studies that are associated with energy systems. Finally, this paper deeply discusses the concept of integration either in the hybrid controlling strategies combining AI with numerical simulation methods or in combining different energy systems in one hybrid model for reliable operation considering the complexity level.

Keywords Artificial intelligence (AI) strategies · Integrated energy systems · Numerical simulation methodologies · Renewable energy sources (RES) · Practical implementations

List of symbols

B	Magnetic field density
μ	Permeability
H	Magnetic field intensity
E	Electric field strength
ε	Permittivity
D	Electric field density

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ρ_v	Volume charge density
J	Current density
σ	Electrical conductivity
v_d	Drift velocity
P	Polarization operator
M	Magnetization operator
φ	Computational region
Z	Vector position function
ϑ	Boundary closed surface
$\lambda(r)$	Integral equation form of potential
r	Position vector of a given computational point
r'	Position vector of a given charge
n	Computational unit vector normal to boundary surface
$K(r, r')$	Mathematical function of green's theorem
$A(r)$	General scalar function of position point vectors
$f(r')$	General form of boundary equation
f_2(r)	Homogenous boundary equation
f_1	Non-Homogenous boundary operator
Ψ	Scalar Form of wave equation
$\hat{n}$	Computational unit vector normal to boundary surface
$G(r, r')$	Mathematical function of green's theorem
$\mathcal{V}$	Bounded computational volume
ζ	Scalar form of variational equation
ξ	Differential computational operator
c	Unknown scalar operational function
x, z	Cartesian coordinate operators
ϱ	Differential computational operator
ϖ	Boundary operator of computational region φ
e	Given computational element
m	Number of computational elements
b, i, j, l	Counter operators
$\hat{c}$	Unknown vector operational function
$\tilde{c}$	Trial-elemental function
T	Transpose process
a	Constant tangential coefficient matrix
Π	Vacuum wave number
S	Electromagnetic wave equation
χ	Refractive index of atmospheric condition
Ω	Sobol-cell body spatial domain
o	Initial value
k	Number of body cells

θ^{I}	Sensitivity index
${}^{`}\Omega_{`0}$	Matrix of state variables
${}^{`}\Omega_{`0\tilde{\omega}}$	Matrix of initial state variables
$\grave{\rho}_{`0}$	Connection matrix of smaller areas
${}^{\prime}\mathrm{E}_{`0}$	Weight matrix
$\partial\, {}^{`}\Omega_{`0}/\partial {}^{`}\mathrm{A}_{`0}$	Matrix of differential parameters of state variables
$\frac{\partial {}^{`}\mathrm{H}_{\breve{\alpha}`0}}{\partial \tilde{\eta}_{\grave{\varepsilon}}}$	Rate of kinetic energy change
$\grave{\hat{\iota}}_{`0}$	Correction operator
$\frac{\partial(\tilde{\ddot{\upsilon}}_{`0})^{2}}{\partial \tilde{\eta}_{\grave{\varepsilon}}}$	Rate of momentum change
$\updownarrow^{\delta}$	Desired solution of regularization equation
$\mathcal{I}$	Singular decomposition system matrix
$\mathcal{L}^{\delta}$	Measured response operator
O	Error coefficient matrix
$\dot{\mathrm{D}}$	Diagonal of matrix
$\mathfrak{I}$	Small singular elemental matrix
W	Input matrix
noi	Error noise operator
p	Number of input elements
β	Non-negative regularization parameter
I	Unit singular matrix
$\mho$	Objective computational function
$h(\tau)$	Forward model function
τ	Model identified parameter
u	Homotopy operator parameter
R	Known operational function
$\mathcal{E}$	Output function of homotopy process
y	Approximate solution function
α	Order indicator of location vectors
γ	Basis function
ς	Number of location points
Ξ	Coefficient formula
C	Differentiation elemental function
$\psi, \varkappa$	Computational matrices
Θ	Jacobian matrix
$Y_{\omega l}$	Calculation coefficient matrix
Y	Potential coefficient matrix
Q	Exerted potential
ω	Given point indicator
L	Number of fictitious charges
$\varnothing$	Unknown vector matrix of fictitious charges

g	Number of contour points
V	Voltage matrix of contour points
$\Gamma_{\gimel}$	Current state hidden layer
$\Gamma_{\gimel-1}$	Previous state known layer
$\lambda_{\gimel}$	Applied input state layer
$\tan\Gamma$	Activation parameter
$\beth_{\gimel\gimel}$	Recurrent neuron layer weight
$\beth_{\text{פ}\gimel}$	Input neuron layer weight
$\mathcal{O}_{\gimel}$	Output neuron layer
$\beth_{\gimel\mathcal{F}}$	Output neuron layer weight
Λ	Net input
$\mathfrak{R}$	Input Signal indicator
$\hbar$	Number of computational layers
$\mathcal{B}$	Link weight indicator
$\}$	Number of input signals
AC	Air-conditioning
ACA	Ant colony algorithm
AI	Artificial intelligence
ANFLN	Adaptive neural fuzzy-logic network
ANN	Artificial neural network
ASAP	Adjoint sensitivity analysis method
BEM	Boundary element method
BFM	Brute–Force method
BPNN	Back propagation neural network
BRA	Bayesian regularization approach
CDs	Corona discharges
CFD	Computational fluid dynamics
CGM	Conjugate gradient method
CNN	Convolutional neural network
CRC	Corona ring configuration
CRT	Classification and regression tree
CSM	Charge simulation method
CST	Compressed sensing technique
DBTL	Dielectric barrier transverse layer
DDM	Direct differentiation method
DFIG	Doubly-fed induction generator
DGM	Diesel generator model
DPM	Death penalty methodology
DSS	Distributed scalar sensor
EET	Elementary effect test
EHV	Extra high voltage

FASTM	Fourier amplitude sensitivity test method
FDM	Finite difference method
FEM	Finite element method
FLCS	Fuzzy-logic controller system
FNN	Feedforward neural network
FSAP	Forward sensitivity analysis method
GA	Genetic algorithm
GNM	Gauss–Newton method
GOL	Generalized opposition learning
GPOA	Greedy pursuit optimization algorithm
GRNN	Generalized regression neural network
GSA	Global sensitivity approach
GWO	Grey wolf optimization
HA	Homotopy algorithm
HIAGA	Hashing integrated adaptive genetic algorithm
HNN	Hopfield neural network
HNP	Hyperbolic needle-to-plane
HOE	High-order elements
HV	High voltage
ICA	Imperialist competitive algorithm
IEs	Integral equations
IM	Iteration methodology
IMSL	International mathematics and statistics library
IOA	Immune optimization algorithm
ISTE	Industrial steam turbine engine
KSONN	Kohonen self organizing neural network
LMM	Levenberg–marquardt method
LSA	Local sensitivity approach
LSQRM	Least squares quick response method
MARSM	Multivariate adaptive regression splines method
MCM	Monte–Carlo method
MFO	Moth flame optimization
MMS	Moving magnet system
MNN	Modular neural network
MPPT	Maximum power point tracking
NPV	Net present value
OWAM	Ordered weighted averaging methodology
PCEM	Polynomial chaos expansion method
PDEs	Partial differential equations
PM	Powell method
PPM	Parameter perturbation method

PSO	Particle swarm optimization
PV	Photo-voltaic
PVR	Partial variance response
RES	Renewable energy sources
RNN	Recurrent neural network
RPFNN	Radial basis functional neural network
RPG	Rod-plane gap
SAA	Simulated annealing method
SAL	Solar array layout
SAM	Spectral analysis methodology
SBO	Satin bowerbird optimization
SDM	Steepest decent method
SR	Spectral regularization
SRCM	Standardized regression coefficient method
SRRCM	Standardized rank regression coefficient method
SVMM	Support vector machine method
TEG	Thermo-electric generator
TRA	Tikhonov regularization approach
TRM	Trust region method
TVR	Total variance response
UIM	Ultraviolet imager methodology
UHV	Ultra-high voltage
VPM	Variation principle methodology
WDF	Weibull distribution function
WOA	Whale optimization algorithm
WTM	Wavelet transform method

1 Introduction

In recent decades, the massive implementation of Artificial Intelligence (AI) strategies into electrical energy field provided effective solutions for several obstacles associated with the efficient operation of electrical networks (Mellit and Kalogirou 2021; Veisi et al. 2022). Economic dispatching, reliability guarantee, quality improvement and infrastructure strengthen of energy networks are the main domains of the integration of AI methodologies into the electrical issues (Abdalla et al. 2021). In these domains, the main roles and challenges of AI strategies considering the energy systems can be highlighted in Table 1 regarding the previous scientific contributions.

Considering the major covered aspects in Table 1, the AI strategies represent the magic wand for supporting the simulation studies to improve the reliable quality of energy systems particularly the operation of RESs.

Since the emergence of AI techniques on the scientific research arena, researchers are still competing in an open challenge to develop the different AI branches for obtaining optimal solutions of several case studies. Regarding energy issues, the AI branches

Table 1 Effective contributions and future challenges of AI strategies within energy systems

Aspect	Roles	Challenges	References
Complicated energy systems	Simplifying optimally the complex mathematical-modelling and simulation of such energy systems	Time waste and unstable operational modes of such systems affect the precise analysis of AI strategies	Mazinan and Khalaji (2016)
Hybrid integration with numerical simulation methods	Enabling these methods to be effectively an optimal planning for pioneering, expert and smart energy systems	The on and off grid scenarios of energy systems affect the controlling response that need powerful simulation software for efficient processing analysis	Naderi et al. (2022), Al-Othman et al. (2022)
Effectiveness assessment	Assessing the empirical studies and measuring simulation effectiveness in studying the complex experimental analysis	Enhancing the performance of AI topologies to avoid the higher difference gap between the experimental results and the hybrid simulation ones	Talaat et al. (2022)
Multi-objective energy systems	Managing several operations and tasks for quality enhancement	The massive number of applied constraints may lead to extreme unacceptable results	Ezzat et al. (2021)
Forecasting and accuracy enhancement	Expecting lost data and measurements to achieve accurate results	Big trained data and importance level of information must be taken into account	Naderi and Asrari (2023) ,Zhu et al. (2022)
Controlling behaviour	Providing an excellent monitor for controlling operational processes	Detecting the importance indices of monitored data to take accurate decisions	Naderi et al. (2022)
Optimization and contingency analysis	Detecting, optimizing and recording the best scenarios for efficient energy systems	Tuning errors and convergence stagnation problems are predominant challenges for obtaining optimum results	Naderi et al. (2023), Zahraee et al. (2016)

are categorized based on the applied-operational methodology into three major types; Artificial Neural Networks (ANNs), Adaptive Neural Fuzzy-Logic Networks (ANFLNs) and computerized optimization algorithms (Abdalla et al. 2021). ANN is a flexible-domain methodology that is inspired from superior operational features and merits of the human brain (Jain et al. 1996; Ghadami et al. 2021; Bienvenido-Huertas et al. 2020). The detailed overview of ANN features, models, applications, and obstacles are expressed in the following sections. ANFLN is a well-known dynamic methodology flourished in the middle of the nineteenth century as a powerful controller to treat with complicated processes that are characterized by little bit mathematical and physical definitions (Lee 1990). As a powerful digital-computerized method, ANFLN is an effective methodology to be massively implemented in electrical issues such as modeling and simplification of electrical networks as will be expressed in the following sections (Fattahi et al. 2016). The prominent boarding of AI methods reached its climax point with the integration of computerized-optimization approaches (Ibrahim et al. 2022). This hybrid combination represents an iconic alternative for analytical methods in solving complex non-linear problems with open and bounded constraints as will be mentioned later (Yang 2020).

Comprehensively, Table 2 expands in highlighting some examples of previous contributions to show the roles of AI branches in the applied studies within energy systems considering the merits and demerits of each contribution.

There are more and more research examples that are strongly similar in terms of idea as well as motivations whereas different in the proposed methodology to achieve this idea (Garud et al. 2021; Mas'ud et al. 1060; Farah et al. 2020).

Regarding the large expansion of the infrastructure of the energy systems as one of the most important polarizing platforms of many electrical issues and phenomena, the degree of complexity in construction and operation has increased affecting directly the quality of the whole network. These obstacles can be summarized into the following points (Ahmad et al. 2020):

- Complicated modeling of network stages leads to massive increase in operations.
- The increase in malfunctions due to intensified magnetic and electrical fields.
- The difficulty to monitor and control the several operational processes.
- The remarkable increase in the overall running cost.
- The difficulty of conducting empirical studies that are related to different stages of the energy networks in case of extreme modes of High Voltage (HV), Extra High Voltage (EHV) and Ultra-High Voltage (UHV) transmission networks.
- Operational obstacles of simulation studies using traditional numerical approaches.
- The tuning errors from the operation of electrical or electronic devices and topologies embedded in the electrical networks for quality control.

Due to the massive bifurcation of conducted studies for these obstacles and the corresponding optimal solutions, it would be difficult to broach such a large number of studies in only one research (Ibrahim et al. 2022). So, there will be a focus shot on the role of numerical simulation modeling and their computational methods in solving the obstacles of energy systems of several domains.

In the past, analytical approaches and their corresponding computational techniques provided effective solutions for several obstacles of electrical networks and issues. As a simple method in processing and evaluation objectives, the functions of analytical methods and their computational techniques can be expressed as follows (Girdinio et al. 1988):

Table 2 Samples of previous contributions showing effect of AI branches within energy systems

References	Contribution	Merits	Demerits
Luo et al. (2023)	Forecasting and estimating the risk rate impacting the trade growth	Reviewing the role of ANN and ANFLN models to enhance the performance of risk assessment for trade	Ignoring the standpoints showing the preference of each proposed AI model over the other
Machesa et al. (2023)	Controlling the non-linear performance of power and torque of Stirling engine with input variables for high efficiency	Providing reasonable studies related to several branches of AI (ANN, ANFLN and ANN-PSO) highlighting the comparative studies for best applied strategy	Ignoring the effect of operational operators of proposed AI strategies on the response and the lack of several hybrid models in the study
Fathi and Parian (2021)	Providing smart hybrid AI models to obtain stable MPPT of PV systems	Using ANFLN, ANN-GA ANN-PSO and ANN-ICA models to get accurate and stable MPPT	The obtained results may be varied with the change in AI operators and constraints
Al Sumarmad et al. (2022)	Assessing stability of microgrid assisted by RES	Reviewing the roles of the controlling strategies of ANN, ANFLN in achieving smart RES energy systems	Ignoring the role of optimization algorithms in improving smartness of proposed strategies

Table 3 Samples of contributions showing effect of numerical methods within energy systems

References	Contribution	Merits	Demerits
Wang et al. (2022)	Simulating a novel hybrid energy system integrated with storage one	Mathematically estimating efficiency, fuel consumption and production rate for a hybrid complex model	Poor comparative studies related to empirical issues
Kapen et al. (2020)	Estimating statistical parameters of WDF to efficiently imitate the operation of wind energy	Providing ten numerical simulation methods to estimate precisely the wave energy produced per month considering the practical measurements	Ignoring the role of AI strategies in obtaining the optimum parameters of WDF
Lv et al. (2017)	Optimizing the SAL design to improve amount of produced solar energy	Providing a hybrid model of GA with simulating numerical method to study the solar energy production	Poor comparative studies related to large scaled hybrid integrated energy systems

- Constructing a well-defined embodied model to imitate simple electrical issues.
- Expressing the constructed models into a meaningful mathematical representation in a simplified form based on the nature of the proposed electrical model or issue.
- Solving the provided mathematical models using the available conventional analytical techniques to validate the effectiveness of the proposed electrical model or issue.

In recent decades, researchers knocked the door of numerical methods to take the lead at the expense of the analytical methods in solving the obstacles of electrical issues. This preference is due to the difficulty in obtaining analytical solutions for complex mathematical models using physical approaches and computerizing the graphical mapping for electrical parameters obtained from analogue modeling techniques. Regarding the need of powerful computing analysis, numerical techniques practically become the most effective choice to compute the complicated operations of different parameters of electrical domains (Elayyan and Abderrazzaq 2005). Table 3 reviews the major previous contributions of numerical methodologies within energy systems.

There are more research examples highlighting the roles of numerical methods within energy systems that are strongly similar in terms of idea and motivated contributions (Chang 2011).

Simulation model is considered as the magic tool to describe the features of electrical issues or phenomena in order to avoid the complexity of assembling experimental components, the highly cost of conducting empirical models with expected dangers (Talaat et al. 2019). These simulation models contribute alongside to conducted experimental studies in enriching the discussion of electrical scientific topics and provide a possible domain to simulate the complex practical electrical issues. As a natural result, these unique features of simulation models paved the way to the appearance of numerical software methods to provide accurate, safe and precise evaluation of different parameters within the integrated energy generation system (Qi et al. 2018).

Numerical analysis is considered as a fertile field for computational methodologies to obtain approximate solutions for complex mathematical problems. Also, it enables the simulation studies to be more effective than the traditional methods in extracting the best solutions in case of complicated electrical issues. Until the fifties of the twentieth century, Numerical methods depended only on manual calculations with a complete absence of the technological analysis. With the development of information revolution and technological advances in the second half of twentieth century, the implementation of the numerical analysis is enriched by computing machine techniques making the analysis fast and economic. In this research, the light will be focused on the classification of numerical methods for the simulation modeling of electrical energy domains. This classification is based on two common factors; the type of solved mathematical equations and the applied constraints. Numerical methods are strongly concerned with the mathematical models of ordinary Partial Differential Equations (PDEs) besides the Integral Equations (IEs) (Ciarlet et al. 1990).

In this context, numerical methods for simulation modeling of electrical energy domains are divided into two major categories. One of them is an open domain method with no limiting boundaries and is applied to solve mathematical models of IEs. The other one of constrained domain that is applied to solve proposed mathematical models of PDEs (Rabah et al. 2017). Based on the nature of the proposed issues to be numerically simulated within the integrated energy generation systems, it is very important to choose the convenient numerical method to be utilized in each study considering the computational requirements of simple representation of complex boundaries in addition to accurate and free-susceptible computation.

Fig. 1 Structural framework of the proposed studies in this research

The firm relation between AI methodologies and the quality control of electrical networks were rooted many years ago thanks to the massive obstacles that were overcome efficiently. The numerical simulation methods form with AI methodologies a powerful tool to obtain the optimal approximate solutions for the most complicated problems in the electrical energy networks either in the presence of any type of constraints or not. In this research, a comprehensive study is provided to show the effective integration of AI approaches in the electrical energy domain with different simulated study issues to overcome the operational problems of different applied numerical methods for efficient quality enhancement (Lee et al. 2022).

In this research, it is worth to be mentioned that the concept of integrated energy systems is related to three common approaches. The first one is to combine different energy generation sources of uneven operational features in one hybrid model. The second one is to combine different controlling strategies with the proposed model of one energy generation system to improve its operation. The third one is to combine several improvement strategies with different energy sources to enhance the reliability of generation. The complexity of integrated energy systems is attributed to high cost of conducting an experimental integration of large-scaled system components, the long processing time of the utilized controlling strategies, the difficulty to simulate the complicated mathematical models considering the applied boundaries and the transformation of digital controlling actions to analogue ones considering the proposed system. Regarding the complicated configuration of integrated energy systems, the provided practical examples in this paper highlight the difference between the two topologies of conventional integrated energy systems and the complex integrated ones.

The main structural framework of this research is divided into four levels as shown in Fig. 1. The fundamental level focuses on reviewing innovatively the operational and mathematical features of the numerical simulation methods within energy domains. The next level discusses the effective role of integrating the AI strategies with the numerical simulation methods to overcome and optimize their obstacles within energy issues. The third level reviews the practical implementation of the combination of AI approaches with numerical simulation methods in several energy issues to show the effectiveness of this hybrid integration highlighting the experimental and simulation studies of energy systems. The final level extracts the concluded points from the provided studies to make innovative

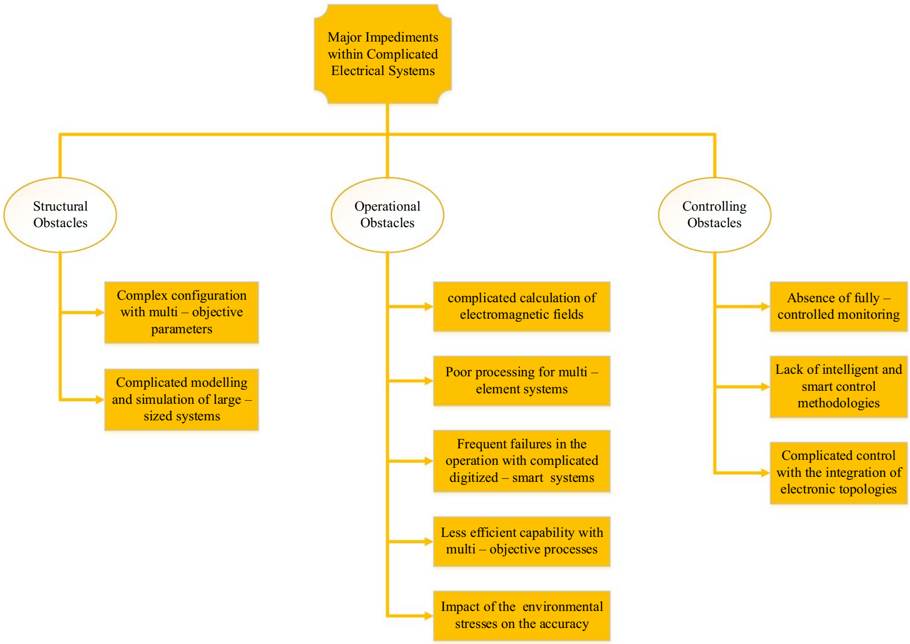


Fig. 2 Major categories of impediments within complicated large-scale electrical systems

discussions highlighting the importance of these studies. All discussions will be organized to pave the way for the upcoming researches to effectively continue the studies in the future.

2 Impact of the numerical methodologies within the complicated electrical domains

2.1 Operational features of numerical approaches over analytical ones

Although the simple operation and fast response of the conventional analytical approaches regarding simple structured electrical systems, they are susceptible to several operational errors collapsing their role in coping with the complicated electrical systems. The operational obstacles within complicated electrical domains are expressed in Fig. 2 (Han and Liu 2017).

Due to the mentioned obstacles in Fig. 2, the numerical approaches are expressed as an iconic alternatives for analyzing the multi-objective processes within the complicated electrical systems (Sevgi 2003). The difficulty in evaluating the values of electromagnetic fields is the most effective reason for the rise of numerical methods on scientific research domain regarding the large-scaled electrical systems. For highlighting the computational impact of numerical methods over traditional ones, Table 4 reviews the major discriminations among them (Sevgi 2003).

Table 4 Analytical methods vs. numerical methods for the simulation of electrical domains

Aspect	Analytical methods	Numerical simulation methods
Operational constraints	The analysis is conducted regarding model constraints and regardless to the software computational ones	Boundaries of obtained parameters and applied software are taken into account in computation process
Computation with system scale	The computation process is based on the modeling of the simple electrical systems of simplified mathematical functions and computerized tasks	Multi-objective tasks and complex computerized analysis are defined in these methods to be studied within the complicated systems
Intelligent control	Due to the computational analysis of simplified models with independent parameters, there is a lack of smart control for the evaluation process	Smart control methodologies using powerful software programs are to be utilized for updating the process of computation
Integration with AI	Limited practical implementations of hybrid models integrating these methods with AI topologies	The utilization of AI methodologies is commonly conducted with these methods for optimal computation
Computational disturbances	Less affected regarding the simplex boundaries of the proposed model and processing domains	Largely affected considering the impact of AI topologies in reducing optimally these errors
Mathematical domains of computation	All processed models are subjected to the mathematical equations of the Maxwell's theorem as a generalized domain of computation	Several domains of computation such as: the mathematical equations of the Maxwell, Green, Huygen, Parabolic and Variational theorems

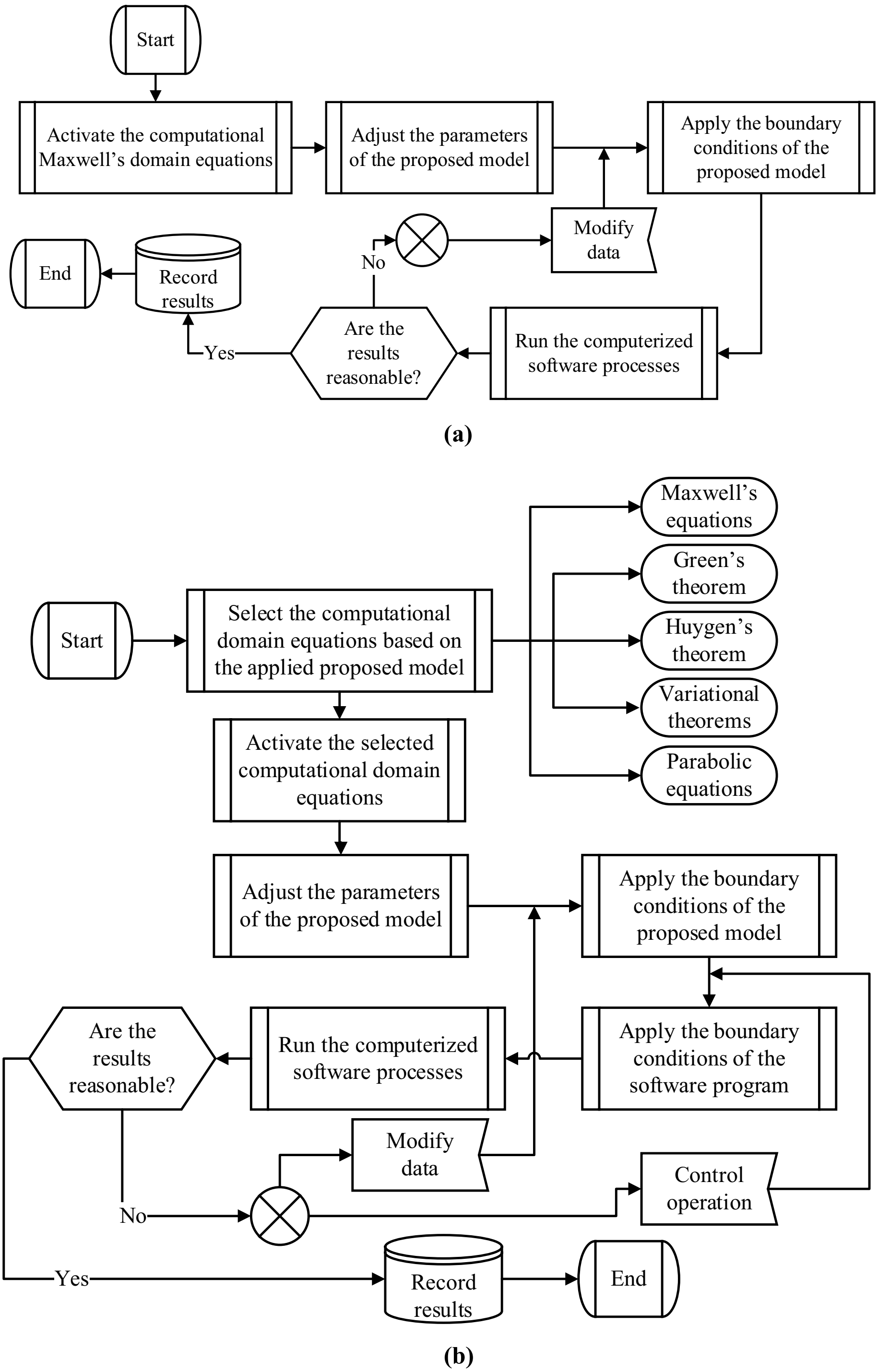


Fig. 3 Computational process flowchart; **a** analytical method, **b** numerical method (Sevgi 2003)

Schematically, the operational methodology of each category may support the comparison to be more comprehensive. Figure 3 illustrates significantly the process of computation for each category regarding the defined aspects in Table 4 (Sevgi 2003).

Regarding Fig. 3, there are some explanations to be comprehensively discussed as follows:

- The operation of the numerical approaches is subjected to two control signals that increase the computational accuracy of these methods over analytical ones regarding the large-sized electrical systems.
- The mapping criterion of the computational domain selection of the numerical method is based on the mathematical representation of the proposed simulation model of the defined system parameters. Manually or using a programmed software, the defined equations of the proposed simulation model either PDEs or IEs and methodologies either iterative or mesh in addition to the electromagnetic domain are to be matched to the suitable computational domain in the side of the utilized numerical method.
- The utilized platform of software program should be a powerful tool to apply the desired operational or controlling tasks regarding the defined system scale.

2.2 Computational domains of numerical approaches

In this context, a comprehensive study for each type of computational domains of numerical approaches is expressed considering the mathematical representation of each domain:

2.2.1 Maxwell's equations

Maxwell's equations are the base structure of the modeling and computation processes of the electromagnetic fields. Maxwell's theorem is mainly subjected to the Curl and Divergence theorems as follows (Jin 2011; Baek et al. 2015):

$$\xrightarrow{\text{Divergence Laws}} \begin{cases} \nabla \cdot \mathrm{B} = \nabla \cdot \mu \mathrm{H} = 0 \ (\textit{Magnetic Concept}) \\ \nabla \cdot \mathrm{D} = \nabla \cdot \varepsilon \mathrm{E} = \rho_v \ (\textit{Electrical Concept}) \end{cases} \tag{1}$$

$$\xrightarrow{\text{Curl Laws}} \begin{cases} \nabla \times \mathrm{H} = \frac{\partial \mathrm{D}}{\partial \mathrm{t}} + \mathrm{J}(\textit{Magnetic Concept}) \\ \nabla \times \mathrm{E} = -\frac{\partial \mathrm{B}}{\partial \mathrm{t}} \ (\textit{Electrical Concept}) \end{cases} \tag{2}$$

For conducting medium with movable charges, the previous equations are supported with some formulas to express the features of these moving charges as follows (Jin 2011; Baek et al. 2015; Guru and Hiziroglu 2009; Hildebrand 2012; Stakgold and Holst 2011):

$$\xrightarrow{\text{Charge Conservation and Current Continuity Laws}} \begin{cases} \nabla \cdot \mathrm{J} + \frac{\partial \rho_v}{\partial \mathrm{t}} = 0 \\ \mathrm{J} = \sigma \mathrm{E} \\ \mathrm{E} = v_d \times \mathrm{B} \end{cases} \tag{3}$$

For dielectric medium, the Maxwell's equations are to be formulated to fit the features of the polarization and magnetization concepts as follows:

$$\xrightarrow{\text{Divergence Laws}} \begin{cases} \nabla \cdot \mathrm{B} = \nabla \cdot \mu \mathrm{H} = 0(\mathit{Magnetic\ Concept}) \\ \nabla \cdot \mathrm{E} = \frac{1}{\varepsilon}\left[\rho_v - (\nabla \cdot \mathrm{P})\right] (\mathit{Electrical\ Concept}) \end{cases} \tag{4}$$

$$\xrightarrow{\text{Curl Laws}} \begin{cases} \nabla \times \mathrm{B} = \mu\left[\left(\varepsilon\frac{\partial \mathrm{D}}{\partial \mathrm{t}}\right) + \mathrm{J} + \frac{\partial \mathrm{P}}{\partial \mathrm{t}} + (\nabla \times \mathrm{M})\right] & (\mathit{Magnetic\ Concept}) \\ \nabla \times \mathrm{E} = -\frac{\partial \mathrm{B}}{\partial \mathrm{t}} & (\mathit{Electrical\ Concept}) \end{cases} \tag{5}$$

2.2.2 Green's theorem

This theorem provides an iconic solution for electrical issues with complex IEs converting them into simple linear equations. This theorem depends mainly on the position; surface and physical concept of bounded medium of the simulated electrical issue (Guru and Hiziroglu 2009). Based on Divergence theorem, the general form of Green's function is expressed as follows:

$$\int_{\text{Region } \varphi} (\nabla \cdot \mathrm{Z})\mathrm{d}\varphi = \oint_{\text{Surface } \vartheta \text{ of Region } \varphi} \mathrm{Z} \cdot \mathrm{d}\vartheta \tag{6}$$

This general form is derived in such manners based on physical structural definition into:

2.2.2.1 Charge simulation concept Green's function is used to simplify the complex integral form of evaluating the electric potential at different positions of the fictitious simulation charges on the surface of a given bounded region as follows (Zhou 2012):

$$\lambda(\mathrm{r}) = \frac{1}{4\pi\varepsilon}\int_{\text{Region } \varphi} \frac{\rho_v(\mathrm{r}')}{|\mathrm{r}-\mathrm{r}'|} d\varphi + \frac{1}{4\pi}\oint_{\text{Surface } \vartheta}\left[\frac{1}{|\mathrm{r}-\mathrm{r}'|}\frac{\partial \lambda}{\partial n} - \lambda\frac{\partial}{\partial n}\left(\frac{1}{|\mathrm{r}-\ \mathrm{r}'|}\right)\right]\mathrm{d}\vartheta \tag{7}$$

2.2.2.2 Mathematical forms of different concepts of boundary conditions Furthermore, Gree's function simplifies the complex non-homogenous integral forms of different boundary conditions regarding the Poisson's boundary condition as follows (Zhou 2012):

Laplacian boundary condition

$$A(\mathrm{r}) = \int_{\text{Region } \varphi} \mathrm{K}(\mathrm{r},\mathrm{r}')\mathrm{f}(\mathrm{r}')\mathrm{d}\varphi + \oint_{\text{Surface } \vartheta}\left[-A(\mathrm{r})\frac{\partial\,\mathrm{K}(\mathrm{r},\mathrm{r}')}{\partial n} + \mathrm{K}(\mathrm{r},\mathrm{r}')\frac{\partial A}{\partial n}\right]\mathrm{d}\vartheta \tag{8}$$

Dirichlet boundary condition

$$A(\mathrm{r}) = \int_{\text{Region } \varphi} \mathrm{K}(\mathrm{r},\mathrm{r}')\mathrm{f}(\mathrm{r}')\mathrm{d}\varphi - \oint_{\text{Surface } \vartheta} A(\mathrm{r})\frac{\partial \mathrm{K}(\mathrm{r},\mathrm{r}')}{\partial n}\mathrm{d}\vartheta \tag{9}$$

Neumann boundary condition

$$A(\mathrm{r}) = \int_{\text{Region } \varphi} \mathrm{K}(\mathrm{r},\mathrm{r}')\mathrm{f}(\mathrm{r}')\mathrm{d}\varphi + \oint_{\text{Surface } \vartheta} \mathrm{K}(\mathrm{r},\mathrm{r}')\frac{\partial A}{\partial n}\mathrm{d}\vartheta \tag{10}$$

Boundary condition of robin problems

$$A(\mathrm{r}) = \int_{\text{Region } \varphi} \mathrm{K}(\mathrm{r}, \mathrm{r}')f(\mathrm{r}')\mathrm{d}\varphi + \oint_{\text{Surface } \vartheta} \frac{f_2(\mathrm{r})}{f_1} \frac{\partial \mathrm{K}(\mathrm{r}, \mathrm{r}')}{\partial n} \mathrm{d}\vartheta \tag{11}$$

Boundary condition of Poisson's equation

$$K(\mathrm{r}, \mathrm{r}') = \frac{1}{4\pi\varepsilon} \frac{1}{|\mathrm{r} - \mathrm{r}'|} \tag{12}$$

2.2.3 Huygen's theorem

Huygen's theorem is related to the modeling of wave equations. This theorem depends on the iterative methodology. The mathematical representation of this theorem is divided into three forms based on the complexity of simulated model as follows (Guru and Hiziroglu 2009; Zhenxiu 2003):

$$\xrightarrow{\text{First Form}} \begin{cases} \Psi(\mathrm{r}') = \oint_{Surface\ \vartheta} \hat{\mathrm{n}} \cdot \left[G(\mathrm{r}, \mathrm{r}')\nabla\Psi(\mathrm{r}) - \Psi(\mathrm{r})\nabla\mathrm{G}(\mathrm{r}, \mathrm{r}')\right]\mathrm{d}\vartheta & \text{if } \mathrm{r}' \in V \\ \oint_{Surface\ \vartheta} \hat{\mathrm{n}} \cdot \left[\mathrm{G}(\mathrm{r}, \mathrm{r}')\nabla\Psi(\mathrm{r}) - \Psi(\mathrm{r})\nabla\mathrm{G}(\mathrm{r}, \mathrm{r}')\right]\mathrm{d}\vartheta = 0 & \text{if } \mathrm{r}' \notin V \end{cases} \tag{13}$$

$$\xrightarrow{\text{Second Form}} \Psi(\mathrm{r}') = -\oint_{\text{Surface } \vartheta} \left[\Psi(r)\hat{\mathrm{n}} \cdot \nabla\mathrm{G}(\mathrm{r}, \mathrm{r}')\right]\mathrm{d}\vartheta \quad \mathrm{r}' \in V \tag{14}$$

$$\xrightarrow{\text{Third Form}} \Psi(\mathrm{r}') = -\oint_{\text{Surface } \vartheta} \left[\mathrm{G}(\mathrm{r}, \mathrm{r}')\hat{\mathrm{n}} \cdot \nabla\Psi(\mathrm{r})\right]\mathrm{d}\vartheta \quad \mathrm{r}' \in V \tag{15}$$

2.2.4 Variational theorems

These theorems are based on dividing the solution domain into small regional elements to facilitate the computation process. The desired solution of the whole complicated system can be obtained by assembling all equations of the divided sub-sectional elements. The methodology of these theorems is based on the following equations (Zienkiewicz et al. 2005):

$$\xrightarrow{\text{General Form}} \zeta = \int_{\text{Region } \varphi} \xi\left(\mathrm{c}, \frac{\mathrm{dc}}{\mathrm{dx}}, \ldots\right)\mathrm{dx} + \varrho\left(\mathrm{c}, \frac{\mathrm{dc}}{\mathrm{dx}}, \ldots\right)\Big|_{\varpi} \tag{16}$$

$$\xrightarrow{\text{General Form with Higher-Order Elements}} \mathrm{c}^{\mathrm{e}} \approx \hat{\mathrm{c}}^{\mathrm{e}} = \sum\nolimits_{\mathrm{b}=1}^{\mathrm{m}} N_b \tilde{c}_b \tag{17}$$

$$\xrightarrow{\text{Derived Equation of One Regional lement Regarding Higher-Orders}} \zeta = -0.5\tilde{\mathrm{c}}^{\mathrm{T}} a\tilde{c} \tag{18}$$

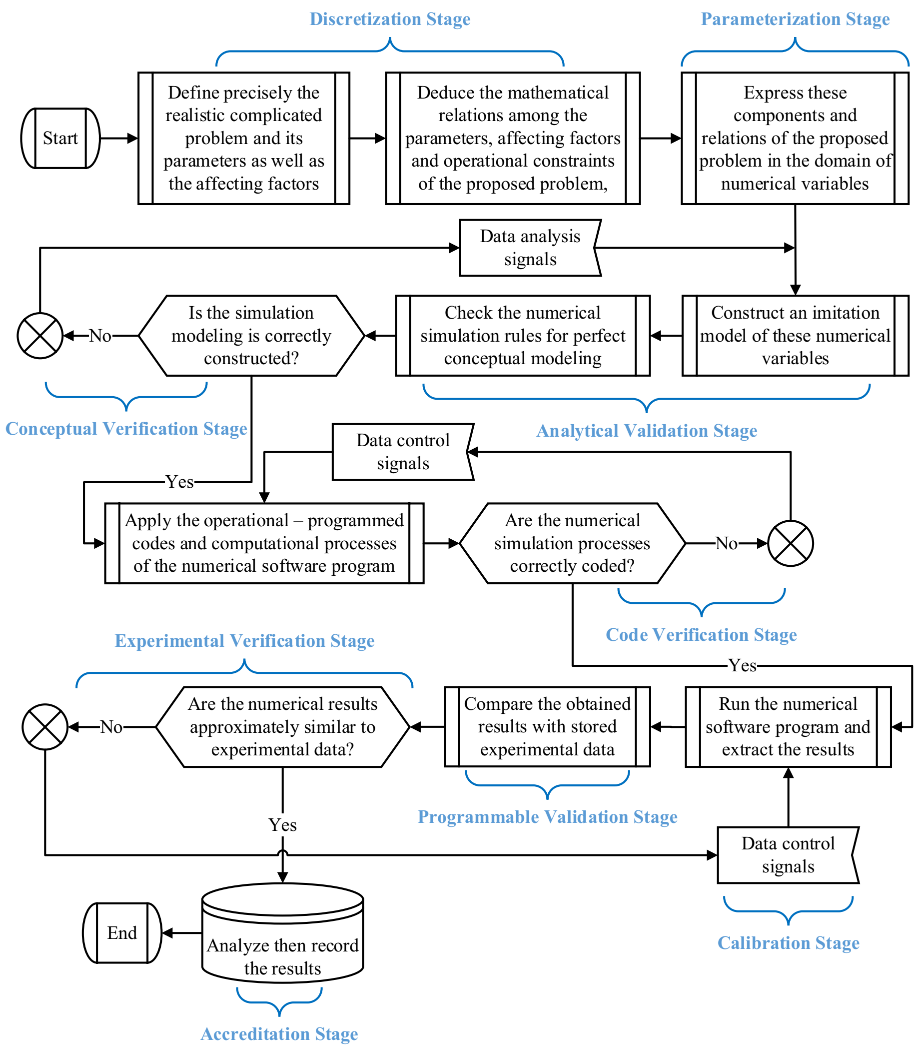


Fig. 4 Methodology flowchart of numerical simulation modeling of a complicated problem

2.2.5 Parabolic equations

These equations are based on the solution of PDEs of wave propagation of electromagnetic fields. The general form of this equation in Cartesian coordinates is expressed as (Gao et al. 2019):

$$\frac{\partial S(x,z)}{\partial x} = \frac{j\Pi}{2}\left[\frac{1}{\Pi^2}\frac{\partial^2}{\partial z^2} + \chi^2(x,z) - 1\right]S(x,z) \tag{19}$$

3 Numerical simulation modeling of complex integrated energy systems

3.1 Operational methodology

Modeling of complex electrical issues is one of the most pioneering trends in the research arena. The modeling simulation is scientifically related to the mathematical embodiment and imitated implementation of any realistic problem. Imitating the dynamic performance of electrical problems requires an effective computerized-numerical methodology to apply the computational simulation (Sevgi 2003; Papas 2014). Schematically, the operational methodology of numerical simulation method is classified into six stages as shown in Fig. 4 (Han and Liu 2017; Sevgi 2003).

Regarding Fig. 4, all the operational stages are programmed in a coded library within a computational platform of a software program such as the embedded library of the Finite Element Method (FEM) in the platform of COMSOL Multiphysics program. Based on this programmable code, data actions or questions in the methodology flowchart are exposed to saved scenarios and operational steps that control the orientation of answer according to the matching criteria with the embedded studies regarding the control actions. Furthermore, the control signals are subjected to the error tolerance within difference counters representing a judgmental tool for accepting the results or controlling the data for optimal solution.

3.2 Types of numerical simulation software programs

There are several categories to classify the numerical simulation software approaches in the domains of electrical energy based on different aspects as follows:

3.2.1 Sensitivity analysis category

This category is based on simulating the proposed model regarding a reasonable tolerance of computational errors that is defined as sensitivity index (Han and Liu 2017). The methodology of this category is computationally based on the precise evaluation of the sensitivity index that arranges the parameters of the simulated problem regarding their importance. The derivation process of the sensitivity index is expressed as (Han and Liu 2017; Sevgi 2003):

$$\xrightarrow{\text{Sampling Step}} \Omega(\mathrm{x}) = \Omega_{\mathrm{o}} + \sum_i \Omega_i(x_i) + \sum_{\substack{1 \le i < j \\ i < j < k}} \Omega_{ij}(x_i, x_j) + \mathrm{HOE} \tag{20}$$

$$\xrightarrow{\text{Evaluation of TVR}} \mathrm{TVR} = \int_0^1 \Omega^2(\mathrm{x})\mathrm{dx} - \Omega^2{}_{\mathrm{o}} \tag{21}$$

$$\xrightarrow{\text{Evaluation of PVR}} \mathrm{PVR} = \int_0^1 \Omega^2{}_{i_1,i_2,\ldots i_q}\left(x_{i_1}, x_{i_2}, \ldots x_{i_q}\right)\mathrm{d}x_{i_1}\mathrm{d}x_{i_2}\ldots\mathrm{d}x_{i_q} \tag{22}$$

$$\xrightarrow{\text{Estimation of Sensitivity Index for Sampled HOE}} \theta^I{}_{HOE} = \mathrm{PVR}/\mathrm{TVR} \tag{23}$$

Table 5 Comparison between the different approaches of sensitivity analysis category

Aspect	LSA	GSA
Applied domain	Estimates the effect of only one changeable parameter of simulated problem on the output response	Estimates the effect of changing multiple parameters of the simulated problem on the output response
Sensitivity index	Derived significantly based on the changeable parameter	Derived based on the change of all simulated parameters simultaneously
Sampling model	Linear-sampling model	Large-scale multi-element model
Merits	Simple operation and calculations	Precise evaluated sensitivity index
Demerits	Fails with irregular and non-linear simulated problems	Large calculations and processing time in addition to the sharp deviation

$$\xrightarrow{\text{Estimation of Sensitivity Index for One Sampled Item}} \theta^{I}(x_i) = 1 - \theta^{I}{}_{HOE} - \theta^{I}{}_{i} \tag{24}$$

The equations are validated in their current formulation for the stationary centralized energy frameworks at stable modes and simple operations. Considering the transient stability and complicated controlling operations of energy systems in case of hybrid integrations, centralized domains are not sufficient for expressing the dynamic behaviour of such complicated systems and the computational equations of sensitivity analysis will be subjected to the mathematical modeling of complex energy system and its constraints. Significantly, the concepts of transient stability assessment and decentralized frameworks of energy systems strongly affect the reformulation of the methodology of computing the sensitivity index. The decentralized frameworks of energy systems are related to the complexity of solving PDEs considering the dynamic behaviour of momentum and kinetic energy. The dynamic decentralized equations of sensitivity analysis can be expressed as follows (Zareian Jahromi et al. 2020):

$$\xrightarrow{\textbf{Defining the matrix of complex PDEs}} [\Omega_{O}] = [\Omega_{O\tilde{\omega}}] - \frac{[\rho_{O}][E_{O}]}{[\partial\Omega_{O}/\partial A_{O}]} \tag{25}$$

$$\xrightarrow{\textbf{Applying the dynamic behaviour}} \frac{\partial H_{\breve{\alpha}O}}{\partial\tilde{\eta}_{\varepsilon}} = \mathbf{0.5}\iota_{O}\frac{\partial(\tilde{\upsilon}_{O})^{2}}{\partial\tilde{\eta}_{\varepsilon}} \tag{26}$$

Then, the sensitivity index is obtained considering the defined mathematical domain of the proposed energy system and their corresponding parameters as well as constraints. Estimation process of sensitivity analysis in decentralized frameworks is related to the comparison of the calculated kinetic energy to the referenced critical one.

This category is sub-divided into two major approaches: Local Sensitivity Approach (LSA) and Global Sensitivity Approach (GSA). An innovative comparison for explaining the basic features of the two approaches is expressed in Table 5 (Han and Liu 2017; Sevgi 2003).

Comprehensively, the classified methods of LSA and GSA are expressed in Fig. 5.

According to the chart shown in Fig. 5, there are six computational methods to be applied for the studies of LSA. The features of these methods are explained in Table 6. Also, the chart shows different applied computational categories for the studies of GSA. Furthermore, this diagram highlights the effectively common sensitivity methods to be utilized in the electrical energy domains with noting that there are many other sensitivity techniques to be used for different studies or integrated models combine these

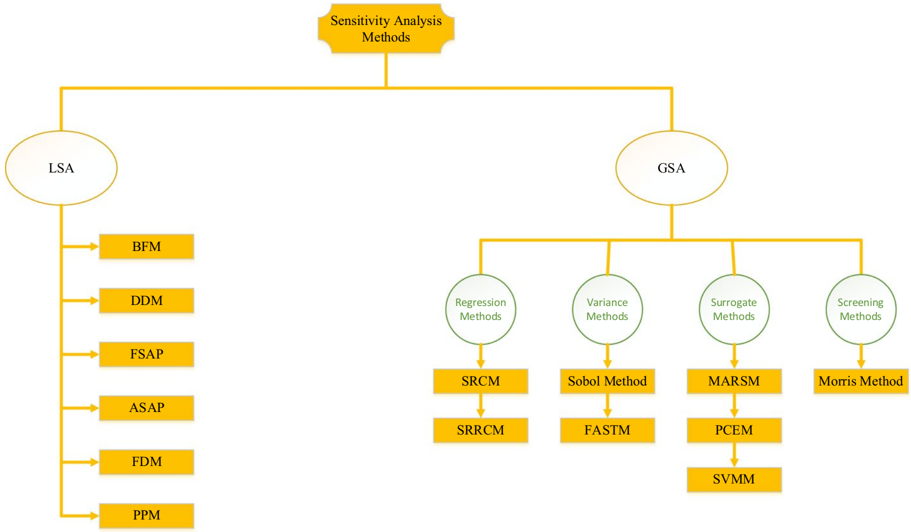


Fig. 5 Classification chart of sensitivity analysis methods

methods with other mentioned ones. To provide a comprehensive study for the GSA categories and their corresponding methods, Table 7 is provided expressing the operational analysis of each category (Han and Liu 2017; Sevgi 2003; Campolongo et al. 2007; Castillo et al. 2006; Sobol 2001; Zhang and Heitjan 2006).

To improve the accuracy of LSA, the different categories of GSA are emerged on scientific area. Significantly, GSA is the natural development of LSA for the emergence of complex problems. With a simple analysis for LSA, researchers usually tend to use the methods of GSA due to iconic features of GSA over LSA for complex problems (Han and Liu 2017; Sevgi 2003; Campolongo et al. 2007; Castillo et al. 2006; Sobol 2001; Zhang and Heitjan 2006).

It is worth to be mentioned that the similarities among LSA methods are summarized into the accurate computation in providing a solution of a unique-characterized model with simple objectives. In spite of the operational simplicity of LSA methods, there is a limited analysis for processing complex objectives with multiple variations regarding the simulation design factors. Significantly, the unique property of each LSA method is based on the ability of processing higher derivatives without disturbances and acceptable sensitivity index.

Regarding Fig. 5, there are four major categories for the operational methods of GSA as an iconic alternative for processing multi-objective models precisely with less number of simulations and complex boundaries. All GSA categories are based on the computation of complex models regarding the operational disturbances. The difficulties of these categories are graded from time consuming to the failure of convergence with operational disturbances within dependent elemental systems. Considering these obstacles, the classified methods of each category are recommended for sampling the domain of complicated models with uneven degree in computational time, sampling capability and accurate operation with less tuning errors. Although the merits of

Table 6 Comparison between the different methods of LSA

Method	Merits	Obstacles	Recommendations
BFM	Simple calculation	Slow analysis for frequent disturbances in the model	It is used for well-defined and computerized models
DDM	Accurate computation	Limited range of dynamic input variations	It is used for derivative parameterized models
FSAP	Quantifying numerical sensitive errors for the physical models	Complicated analysis for multi-dimensional and large parameters	It is used for models with simple derivative equations based on time variance
ASAP	Ease analysis for large, parameterized models with simple objectives	Poor response for various times due to the complex discretization process	It is used for models with a set of various components to be functionally derivate
FDM	Higher accuracy for computing HOE with a simple division way	Large and complicated boundaries for various elements of the model	It is used with models with a set of large derivate HOE to be approximately solved
PPM	Precise computation compared to its simple structure and analysis	Dealing with Limited constraints for several mathematical models	It is used for compact and complex physical or mathematical models

Table 7 Comparison between the different categories of GSA

Series	Features	Merits	Obstacles	Methods	Recommendations
RM category	Deals with the large models of a uniform variance for independent parameters	Simple calculation with a moderate response	Fails to provide reasonable accuracy for dependent parameterized models	SRRCM	Used for linear variance models
				SRRCM	Used for irregular variance models
VM category	Deals with the discrete variance of the model parameters regarding the design factors	Precise response in case of combined parameters	Large processing time and complex analysis for sampling calculation of the discrete parameters	Sobol Method	Suitable to be used for sampling computation
				FASTM	Suitable for compact computation with varying factors
SM category	Is the only one to establish the mathematical model then provide the calculation analysis in an accurate manner	The most efficient one to deal with complex models	Expected disturbances on the response due to the complex constraints of model parameters	MARSM	Used for improving operational analysis of RM category
				PCEM	Used for minimizing the sampling errors of HOE to increase the computation accuracy
				SVMM	Used for increasing the effectiveness of complicated machine processed models
SA category	Randomly used one as it is only used for discrete estimation of model parameters	Ease calculation and simple evaluation domain	Limited analysis as it is used for simple parameterized models with no varying factors	Morris Method	Only computational domain of this category that provides accurate response for simple models whereas fails to sample the complex models

sensitivity analysis methods, its reliability decreases sharply due to the massive disturbances in output response for irregular issues (Han and Liu 2017).

3.2.2 Regularization category

This category can be generally applied for one of the following points to increase accuracy of numerical simulation and parameterization (Engl et al. 1996; Sun et al. 2014):

- There are ill-defined or non-subsistent parameters within the simulated model.
- The numerical simulation process is unstable for non-linear problems.
- There is a noise due to the massive disturbances in the output response.
- The existence of multi-variations that leads to discontinuous linearity in response.

The mathematical definition of this category is based on the following formula (Han and Liu 2017):

$$\ell^{\delta} = \mathrm{I}^{-1}\mathrm{L}^{\delta} = \mathrm{O}\dot{D}(\mathfrak{I}^{-1})\mathrm{W}^{\mathrm{T}}[\mathrm{W}\dot{D}(\mathfrak{I})\mathrm{O}^{\mathrm{T}}\ell + \mathrm{noi}] = \ell + \sum_{i=1}^{p}\mathfrak{I}_i^{-1}(\mathrm{w_i}^{\mathrm{T}}\cdot\mathrm{noi})\mathrm{o_i} \tag{27}$$

The most effective factors on the operational response of this category are noise and error coefficient singular matrix that affect the computational effectiveness. Comprehensively, the different methods of regularization category are listed in Fig. 6 (Han and Liu 2017; Sun et al. 2014).

Significantly, the main distinguishable factors between these categories are based on reducing computational errors that are related to ill-defined parameters, noise and derived error coefficient singular matrix. Furthermore, these computational errors are minimized using derived objective functions from the general form in Eq. (25) regarding the application of stability constraints. These objectives and corresponding constraints are expressed as (Han and Liu 2017):

$$\xrightarrow{\text{VPM Category}} \ell^{\beta,\,\delta} = [I^T I + \beta I]^{-1} I^T L^{\delta} \xrightarrow{\text{under constrints}} \left\| L^{\delta} - I\ell \right\| \; \|\ell\| \tag{28}$$

$$\xrightarrow{\text{SAM Category}} \ell^{\beta,\delta} = \sum_{\mathfrak{I}^2 \geq \beta} \mathfrak{I}_i^{-1}\left[w_i{}^T L^{\delta}\right] o_i \xrightarrow{\text{under constrints}} \left\| 1 - \frac{4}{\pi}\tan^{-1}\left(e^{-\frac{\mathfrak{I}}{\beta}}\right) \right\| \tag{29}$$

$$\xrightarrow{\text{IM Category}} L^{\delta} = \mathfrak{I}\ell + \mathrm{noi} \xrightarrow{\text{under constrints}} \|\,\ell^{*}\| \tag{30}$$

Mainly, the effective factor to discriminate between the methods of each methodology is the arithmetic programming manner for simulating the objective function and boundaries of the proposed model (Tarantola and Valette 1982). Using computerized codes, the basic operational methodology of the regularization method is subjected to embedded criteria in a programmed platform to control the data and signals, see Fig. 7.

Despite the enough points about regularization methods that are described, it is necessary to show that the major classification methods of IM category are considered the most common ones due to their various merits, obstacles and applications over the other methodologies as shown in Table 8. The sub-classified methods that are branched from the major ones of IM categories are subjected to the same assumption of ignoring the

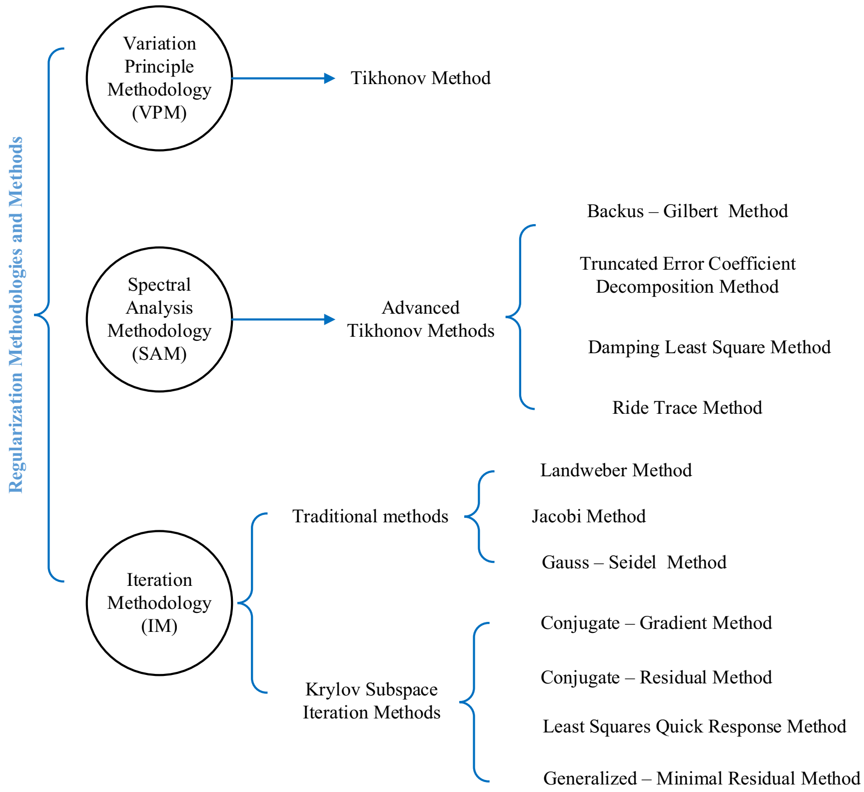


Fig. 6 Comprehensive classifications of regularization methods

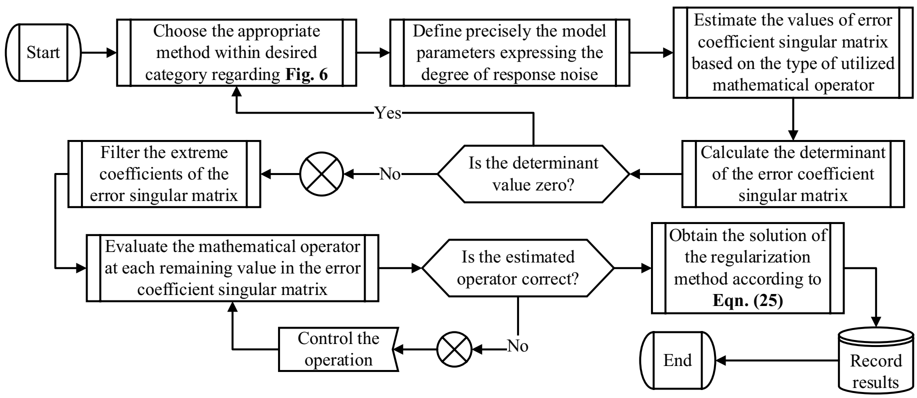


Fig. 7 The basic operational methodology of the regularization method

Table 8 Comparison between the major classified-methods of IM of regularization category

	Methods	Merits	Obstacles	Recommendations
IM category	Traditional methods	Simple calculation with improving stability of response better than sensitivity and regularization methods	Low speed of convergence and processing time in case of complicated problems	These methods are used for a limited number of linear applications due to their massive obstacles
	Krylov Subspace iteration methods	Storing large data in a less required memory and high speed of convergence with a higher stability	Easy to diverge with low frequency noise and high iteration step	Used for solving the complicated problems in linear and non-linear modes

discrimination criterion of the programming process in the electrical engineering studies (Han and Liu 2017; Engl et al. 1996; Sun et al. 2014; Tarantola and Valette 1982).

3.2.3 Inverse computational approaches

This category is the most effective one to completely define the parameters of the proposed problem, cover comprehensively the overall constraints of the parameterized model as well as the simulation software and increase computational stability of numerical response. The bifurcation of this category in the domains of electrical energy are considered as the most massive one at all among the other different categories of numerical simulation software programs as shown in Fig. 8 (Aster et al. 2018).

3.2.3.1 Gradient iteration methods These methods are one of the earliest computational approaches to simply obtain the inverse arithmetic solutions for the complicated problems based on the following merits (Aster et al. 2018):

- Optimizing the objective function of the simulated model based only on the positions and directions of the search steps without any complicated controlling processes.
- Converging the computational response whatever the analyzed complicated problems.
- The massive variety of programmable software programs related to the computation of these methods such as International Mathematics and Statistics Library (IMSL).
- Applying the iterative methodologies to avoid large simulated blocks, ensure the stability of the computation and increase the accuracy regarding tuning errors.

Significantly, the iterative methodologies of these techniques depend on the Homotopy Algorithm (HA) for processing the objective function of the simulated complicated model. HA is a tracing and scrutinizing methodology for the response path of the computational analysis. This algorithm involves four major operational stages as shown in Fig. 9 (Liu and

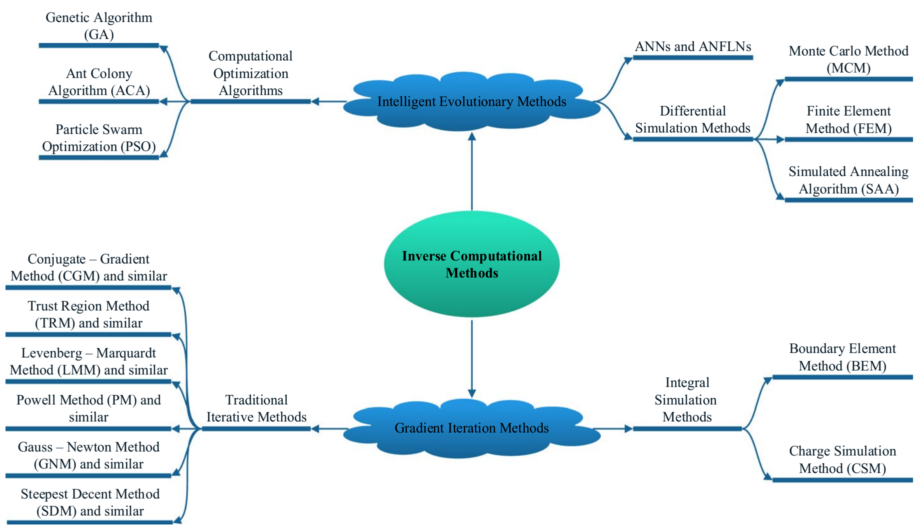


Fig. 8 Classification of inverse computational methods in electrical energy domains

Han 2003). The initial points of numerical computation are obtained in the initialization stage. Choosing the optimal step length and tracing direction are processed in the forecasting stage based on Euler's approach. Testing the effectiveness of the optimally

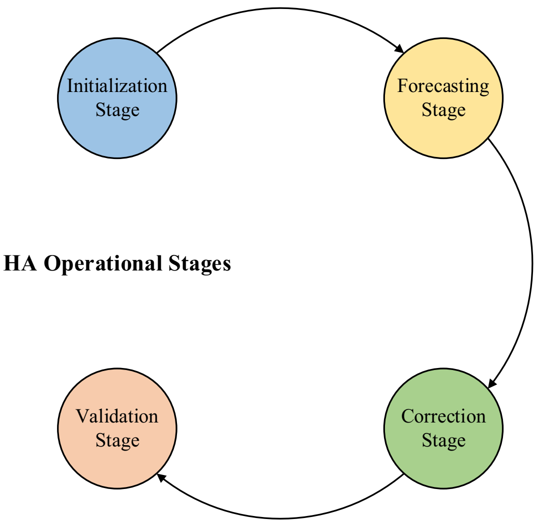


Fig. 9 Sequential operational stages of HA

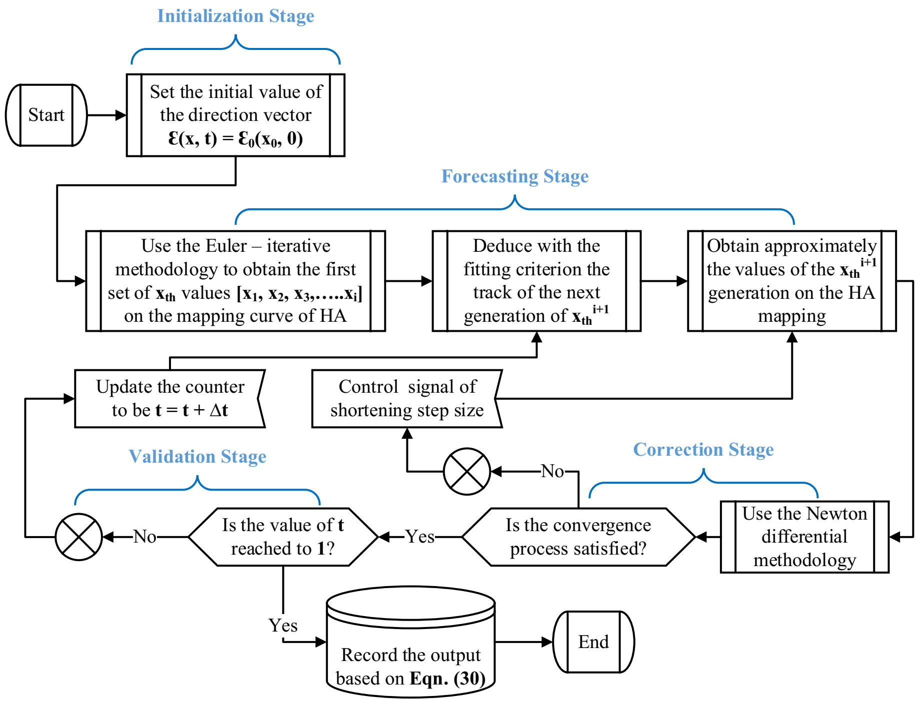


Fig. 10 The operational methodology flowchart of HA performance

forecasted data is embedded in correction stage based on Newton-adoption approach. Checking the convergence process and validity of the results are expressed in validation stage, see Fig. 10 (Liu and Han 2003).

To innovatively describe the computational methodology and stages of HA, the mathematical modeling of HA must be expressed based on the following formulas (Han and Liu 2017):

$$\xrightarrow[]{\substack{\text{The General Non - Linear Expression of the Mathematical}\\ \text{Objective Function to Be Processed}}} (\tau) = h(\tau) - L^{\delta} \tag{31}$$

$$\xrightarrow[]{\substack{\text{The Applied Mathematical Modeling Function of HA}\\ \text{for The Model Objective Function}}} \varepsilon(\tau, u) = u[(\tau)] + (1-u)[R(\tau)] \tag{32}$$

Deepening more into the properties of HA, the following innovatively expressed points will show the performance and applications of this algorithm:

- This algorithm is one of the most iconic methodologies for the computation of simple non-linear mathematical modeling formulas.
- It is suitable for the iterative computation due to its comprehensive convergence with a global set of converged-computations for any applied initial arithmetic point.
- This algorithm experiences a poor performance for sophisticated non-linear models due to the difficulty in computing just complicated derived-mathematical equations

Regarding the embedded data as well as programmed strategies within a software program, the applied questions and actions are accredited in the suitable orientation.

Traditional iterative methods Regarding Fig. 8, the traditional iterative methods are one of the most common numerical simulation methods with a several bifurcated classes (Aster et al. 2018). The merits of all classes are almost the same involving the convergence capability for non-linear, ill-defined and large-scale simulated problems. The other advantages are based on fast response and stagnation to get the optimal solutions with higher accuracy. Furthermore, the obstacles of the classes are mainly related to large number of iterations, time waste, slow convergence and simulation failure regarding the applied constraints for large-scale parameters. The recommendations of these methods are associated with simple structural models and simulated grids (Aster et al. 2018)

Regarding the domain of energy systems and the electrical nature of solved problems inspired from the practical power grids as shown in Fig. 8, the traditional iterative methods are categorized into six major classes addressed by the most common pioneering method of each class. The features of these classes are to be innovatively expressed in Table 9 (Han and Liu 2017; Aster et al. 2018; Liu and Han 2003).

Integral simulation methods Considering Fig. 8, the integral simulation methods are classified into two common major types. These types provide effective solutions for the complex obstacles of electromagnetic fields. The discrimination between CSM and BEM is expressed innovatively in Table 10 regarding the role of iterative methodology (Han and Liu 2017; Wu 2019; Talaat et al. 2020).

Based on programmed software code, the applied actions through structural methodologies as mentioned in Table 10 are answered in a suitable orientation regarding validation criteria.w

Table 9 Comparison between the traditional iterative classes in electrical engineering domain

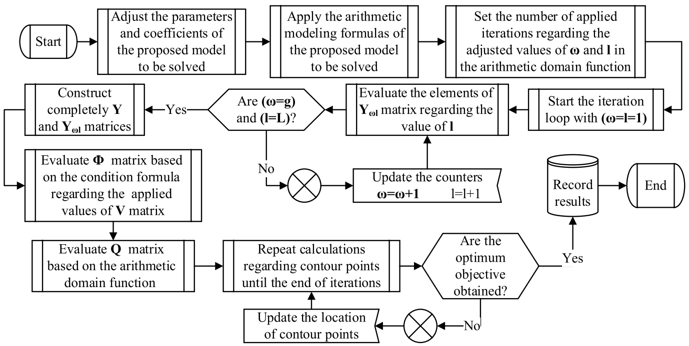
Class	Merits	Obstacles	Recommendations
CGM	Reasonable convergence and good optimization of large-scale quadratic functional problems	Massive iterations to reach to minimum stagnation leading to divergence before obtaining solution	Solving linear or non-linear problems and regularization of quadratic functions
TRM	Vigorous solver with a compact manner to search the optimal approximate non-linear solutions	Diverge with constrained non–linear problems and if initial searching point is far from optimal solution	Solving unconstrained non-linear and ill-defined problems with a reliable convergence
LMM	Robust algorithm, fast response and powerful ability to get the optimal solution of diverged initial searching point	Slow convergence for very large-parameterized problems and smooth derivatives of ill-defined tracking points	It is used for parameter extraction and get the optimal solution based on converged mixture of CGM with SDM
PM	Simple operation and gets optimal solution for ill–defined problems	Very slow convergence	It is used for constrained problems and parameter sampling processes
GNM	Higher and fast convergence stagnation for large parameterized problems or models	Poor performance for illl-defined problems and divergence in case of the larger searching step size	Obtaining optimal solutions for non-linear and least squared–parameterized models
SDM	Reliable convergence for complex problems, simple computation and low required storage memories	Slow convergence for constrained problems and response disturbances in case of larger step size	Solving complicated integral functionally problems such as machine learning

Table 10 Comparison among the iteratively integral simulation methods within electrical domain

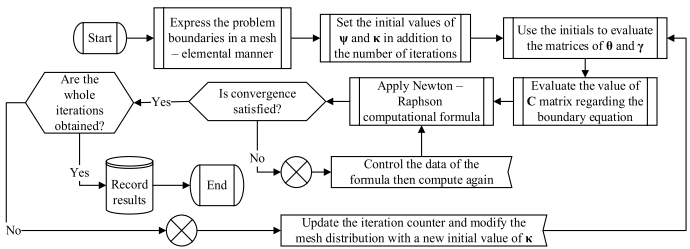
Aspect	BEM with iterative approach	CSM with iterative approach
Usage	BEM is utilized to overcome the computational problems of actual electromagnetic or mechanical fields with complex boundaries of the PDEs	CSM is utilized to overcome the computational problems of actual complicated electromagnetic fields with an open domain of boundaries
Operation principle	BEM depends on modifying the simulated constraints of the PDEs of the practical field to fit the domain of the arithmetic software and substituting these new fitted constraints into the integral mathematical modelling form of the simulated problem to easily obtain the optimal solution instead of the complicated bounded PDEs	CSM is based on simulating the practical electromagnetic field by several fictitious charges of any shaped-types in a given region and computing the electrostatic potential exerted at any point in that region by obtaining precisely the sum of the potentials experienced from these individual fictitious charges
Applications	Electromagnetics and fluid mechanics	Electromagnetics and HV Issues
Iterative role	Enhancing the convergence processing time for complex constrained problems	Improving the searching manner for obtaining accurate optimal solutions
Arithmetic domain function	The approximate solution of BEM is subjected to the following formula based on the linearity of the system: $\mathrm{y}_{\alpha}(\mathrm{x}) = \sum_{j=1}^{\varsigma} \Xi_j \gamma_{\alpha}^{j}(x)$ *Regarding the boundary equation of:* $\mathrm{C} = \Xi\psi - \gamma\varkappa$	The potential computational formula at any point within a given region of any-shaped fictitious charges: $\mathrm{Q}_{\omega} = \sum_{l=1}^{L} Y_{\omega l}\varnothing_l \omega = 1, 2, 3, \ldots, \mathrm{g}$ *Regarding the condition equation of:* $\varnothing = [Y]^{-1}[V]$
Validation criterion	Satisfying the convergence based on Newton–Raphson differential method of evaluation equation: $\varkappa = \varkappa + \Theta^{-1}C$	Satisfying the optimum objective of: $\sum_{\omega=1}^{g} \left[V - \mathrm{Q}_{\omega}\right]^2$ based on the location of contour points
Essential evaluation conditions	Expressing the problem boundaries in a mesh-elemental shape and evaluating the matrices of $\boldsymbol{\theta}$ and $\boldsymbol{\gamma}$	Calculating the values of the matrices $\boldsymbol{Y}_{\boldsymbol{\omega l}}$ and $\boldsymbol{Y}$ regarding the number of contour points

Table 10 (continued)

Aspect	BEM with iterative approach	CSM with iterative approach
Structural methodology	*CSM with iterative methodology*	



BEM with iterative methodology



Intelligent evolutionary methods In spite of the merits of gradient iteration methods, there are several obstacles as follows (Han and Liu 2017):

- The operational incompetence in case of large-parameterized complicated problems due to the exaggerated needed number of iterations and low processing response.
- The convergence shortages and slow operation for evaluating non-linear problems.
- The difficulty in determining the initial guess point and the optimum step size for the integral simulation methods negatively affects the accurate computation.

To overcome these obstacles, intelligent evolutionary methods are provided as a magic tool to enhance the overall efficiency of inverse computational category. The merits, obstacles and recommendations of these methods can be listed as shown in Fig. 11.

ANNs and ANFLNs Considering Fig. 11, a comprehensive overview for ANNs and ANFLNs operational features are provided in Table 11 (Talaat et al. 2022; Han and Liu 2017). Significantly, ANNs are smart functionally systems at which their operational nature inspired from the transmission manner of electrical signals between the nerve cells. On the other side, ANFLNs are logical control systems that mimic the human thinking to dominate the electrical signals among nerve cells. ANNs are utilized in medical and energy domains such as voice recognition and medical diagnosis whereas ANFLNs are used in controllable energy systems such as robotics and automation.

Based on the embedded data in a programmed software code, the applied questions and actions through the structural methodologies that are mentioned in Table 4 are answered in a suitable orientation regarding the validation criteria.

Differential simulation methods Considering Fig. 8, these methods are categorized into three effective approaches. These approaches inspired their operational performance either practically for SAA regarding the melting and cooling behaviour of a body or statistically for MCM regarding the estimated risks within contingency analysis. Furthermore, FEM is based on mesh generation concept for simplifying the large-scale systems. With higher accuracy, these approaches deal with non-uniform shaped models; multi-sampled and random complex models especially for electromagnetic issues.

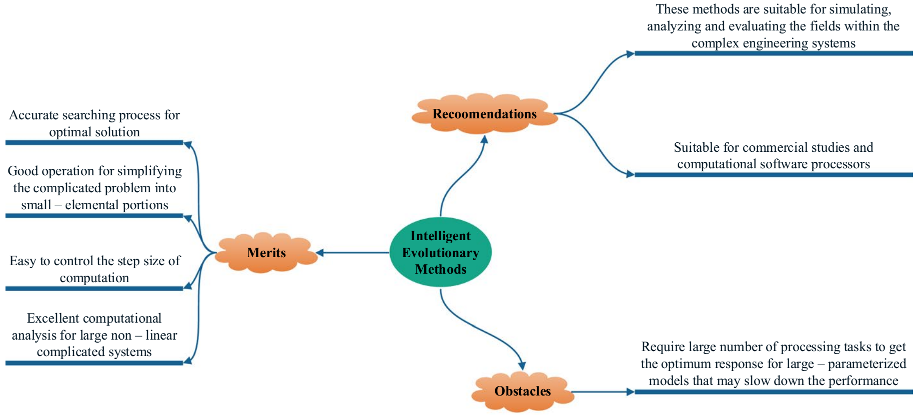


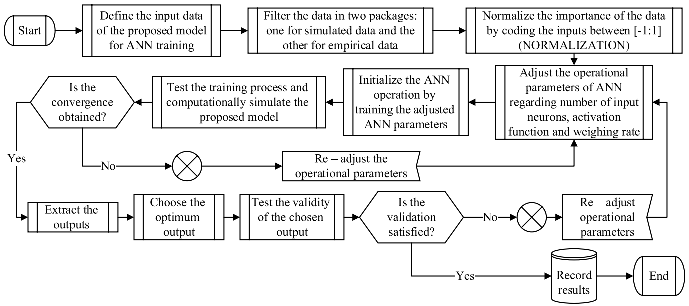
Fig. 11 Major properties of intelligent evolutionary methods within electrical domains

Table 11 Overview on ANNs and ANFLNs regarding the electrical domains

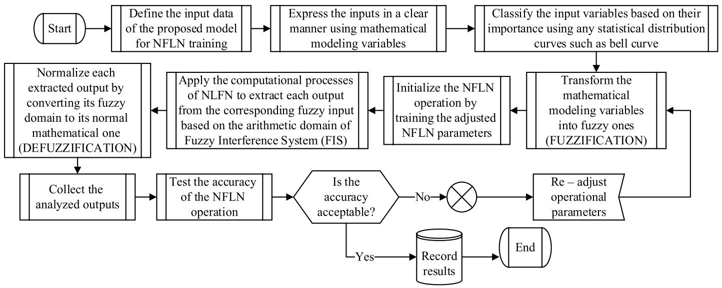
Aspect	ANNs	ANFLNs
Operation principle	ANNs depend on multi-functional patterns, memorizing and calculation of the non-linear operation of elemental neurons. ANNs depend on operational weighing level of each neuron	ANFLNs depend on extracting the features of ANNs to control neuron functions based on analysing input and output signals through nerve cells pattern using powerful algorithms
Computational coefficient factors	Weighing level of the neuron, the chosen elemental neuron and the non-linear transfer formula of ANN	Output disturbances, controlling criteria and interference mechanism among input-output data
Essential computations	Successful transformation of the input variables to the coding language of the software processing program	Successful transformation from modeling variables to fuzzy ones and vice-versa
Arithmetic Domain Function	The non-linear transfer formula $\boldsymbol{\Gamma}_{\gimel} = \boldsymbol{f}(\boldsymbol{\Gamma}_{\gimel-\mathbf{1}}, \wedge_{\gimel}) =$ $[\mathbf{tan}\,\boldsymbol{\Gamma}]\ [\beth_{\gimel\gimel}\boldsymbol{\Gamma}_{\gimel-\mathbf{1}} + \beth_{\text{פ}\gimel}\wedge_{\gimel}]$ *Regarding the criterion function of choosing the layer of elemental node:* w	(a) linguistic input nodes; (b) term input nodes; (c) rule nodes; (d) term nodes; (e) linguistic output nodes *Regarding the objective formula:* $\Lambda = f\begin{cases} \mathfrak{R}_1^{(\hbar)}, \mathfrak{R}_2^{(\hbar)}, \mathfrak{R}_3^{(\hbar)}, \ldots, \mathfrak{R}_{\}}^{(\hbar)} \\ \mathcal{B}_1^{(\hbar)}, \mathcal{B}_2^{(\hbar)}, \mathcal{B}_3^{(\hbar)}, \ldots, \mathcal{B}_{\}}^{(\hbar)} \end{cases}$
Computational shaped-configuration	(a) MNN; (b) RNN; (c) HNN; (d) CNN; (c) RPFNN; (f) KSONN; (g) BPNN; (h) GRNN and (i) FNN	(a) Cooperative ANFLN; (b) Concurrent ANFLN and (c) Hybrid ANFLN
Discrimination criteria among types	Travelling distance of transmitted data, location of each neuron variable in map pattern, number of hidden layers	Time sequence between ANN processing and fuzzy operation and applied algorithms

Table 11 (continued)

Aspect	ANNs	ANFLNs
Structural methodology	*ANN methodology regarding specific parameters of each configuration type*	



ANFLN methodology regarding specific parameters of each configuration type



Regarding operational factors, these approaches depend in an uneven manner on the complexity of simulated models, applied constraints and operational stability.

Computational optimization algorithms Considering Fig. 8, these algorithms are smart computerized tools imitating natural behavior of practical embodiments such as natural selection process for GA, searching process for the position of food supply for ACA and sudden orientation for PSO. The searching domain of these algorithms is mainly meta-heuristic with a probabilistic mathematical behavior. The merits of these algorithms are based in an uneven degree on the fast processing response and less number of iterations for large scale objective functions. The deviated disturbances in the optimized results and time waste for complex multi-objectives are the main obstacles for these algorithms. The computational operators vary definitely for each algorithm. For GA, the crossover as well as mutation processes are the main operators whereas clustering and searching speed processes are the main ones regarding the optimal studies (Nguyen and Jung 2021).

Significantly, the hybrid methods provide an effective solution for complicated energy problems. These hybrid combination methods involve multiple aspects such as:

- Optimization algorithms assisted by ANNs to increase accuracy of global searching.
- Gradient iteration methods assisted with ANFLN to increase the convergence.
- Bayesian methodologies assisted with the evolutionary optimization algorithms.

4 Numerical simulation methods with ANNs for integrated energy issues

4.1 Sensitivity approaches with ANNs; illustrative and prospective practical examples

The integration of ANNs with the operational analysis of sensitivity simulation approaches generally provides the following merits:

- Precisely estimating the sensitivity indices with less operational disturbances.
- Enabling the sensitivity approaches to forecast the influence of the coefficient factors on the operation of different electrical systems.
- Optimizing the number of effective factors within any electrical system and arranging the coefficient factors based on their impact degree.
- Enhancing the reliability and efficiency of different electrical issues or systems.

4.1.1 Integrated strategy of sensitivity analysis with ANNs within energy system

4.1.1.1 Improving and optimizing the operation of photo–voltaic (PV) modules In this practical experimental study, the proposed framework is to integrate the sensitivity analysis with ANNs in one hybrid controlling model to enhance the generation features of the Photo-Voltaic (PV) energy system. As one of the most effective energy generation systems to practically exploit the solar effect, PV networks require more enhancements to achieve a sufficient accuracy to be a vital source in the energy generation market (Bazilian et al. 2013; Tzuc et al. 2019). Considering this conducted study, the obstacles of PV systems can be expressed as follows (Tzuc et al. 2019):

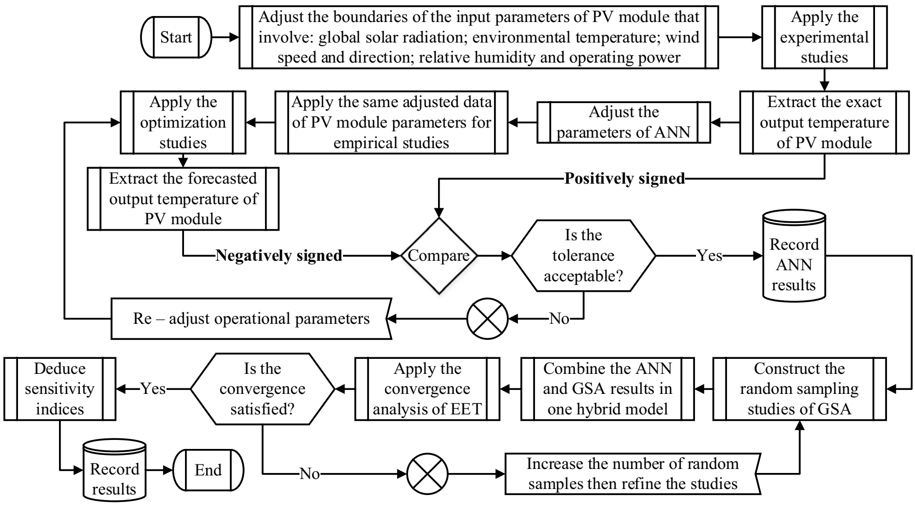


Fig. 12 Methodology of integrated GSA with ANNs for improving operation of PV module

- At the highest level of energy conversion, the generated electricity from PV modules do not exceed 15% from the total incident solar radiation lines resulting in the need of large number of PV modules to obtain the desired amount of electricity.
- The massive amount of heat dissipation affects the operation of PV modules by minimizing the operational voltage and power of the output generated electricity.
- The longtime of exposure to solar radiation increases the temperature of PV modules above the acceptable limit that may lead to the operational damage of these modules.

In this study, a computational forecasting-optimization software is constructed to precisely predict the temperature level of PV modules. This software arranges optimally the impact degrees of estimated temperatures to improve the overall generation efficiency of PV energy system. The hybrid integration of GSA with ANNs is provided in this study as a powerful computerized software to enhance the experimental operation of PV modules regarding Fig. 12 (Tzuc et al. 2019). The effectiveness of the controlling results of this integrated strategy is validated considering the Elementary Effect Test (EET). Regarding EET, the ambient temperature and solar radiations are the most effective factors on the operation of PV modules (Tzuc et al. 2019).

Considering the performed studies, the achieved targets can be expressed as follows:

- Validating the effectiveness of EET to detect the most influential parameters on the PV module based on the sensitivity index of each parameter.
- Confirming arithmetically and graphically that the increase in the studied random samples of GSA decreases deviations in the performance of PV module parameters.
- Prospectively, integrating different methods of GSA with ANNs may affect response of the forecasting and optimization processes to provide advanced future studies.

4.1.1.2 Improving the operational feasibility and reliability of wind power generation In this practical simulation study, the proposed framework is to integrate the hybrid model of

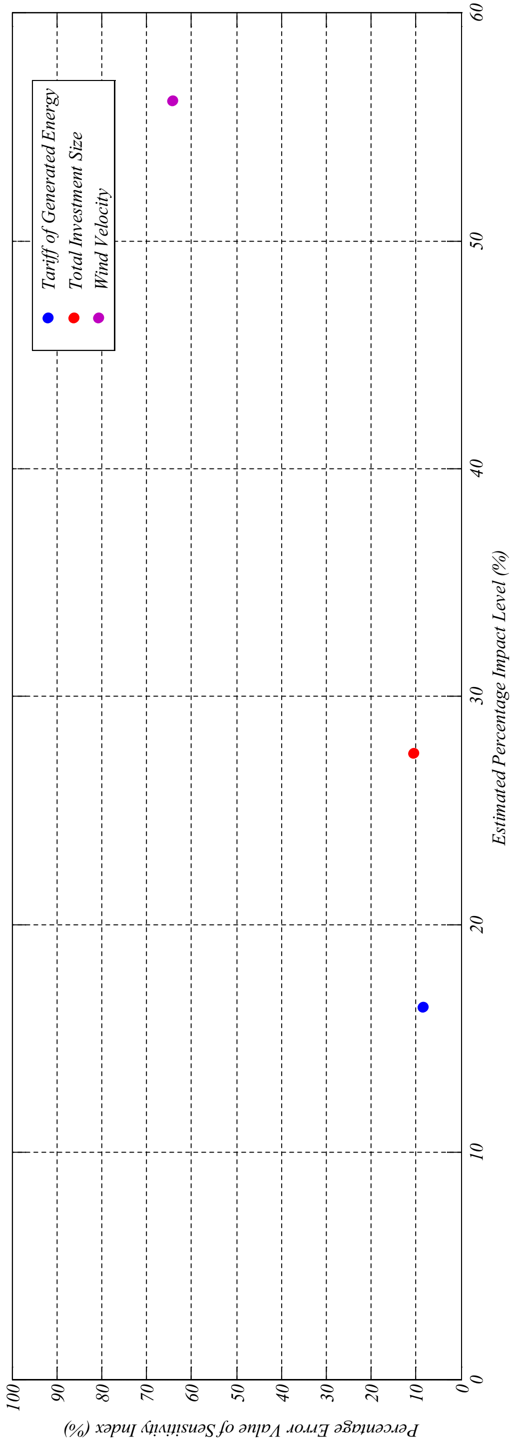


Fig. 13 The results of proposed model for improving the operation of wind energy system

Table 12 Generation analysis of integrated energy sources for practical and controlling scenarios

Parameter	FPGA	FPGA with ANN	Maximum percentage deviation (%)
Voltage profile	12.14805 V	11.721 V	3.51538
Current profile	9.23425 A	11.34385 A	22.84535
Power profile	112.2963 W	136.1829 W	21.271

sensitivity analysis and ANNs with NPV strategy to enhance the generation features of the wind energy system. To improve the reliability and profitability of wind energy systems, it is necessary to identify the impact of coefficients that affect the operation of these systems. Regarding this study, the proposed integrated controlling strategy is provided to detect the most influential parameters on the operation of wind energy systems (Rotela Junior et al. 2281).

The economic feasibility for constructing an efficient wind energy system is a major obstacle for the reliability of these systems in addition to the sudden changes in their parameterized variables and factors. The recent studies provide NPV method as a powerful methodology to be integrated with the hybrid model of sensitivity analysis and ANNs to determine the impact of financial and operational parameters of wind energy system (Rotela Junior et al. 2281). The proposed model improves the reliability of wind system regarding the following achieved targets (Rotela Junior et al. 2281):

- The most influential factors on the operation of wind energy system are tariff of generated energy, wind velocity and the total investment size.
- NPV indicator detects that the most effective factor is the wind velocity.
- The usage of ANNs is numerically classifying the impact levels of the influential factors to validate the performance of NPV approach as shown in Fig. 13.

4.1.1.3 Impact of ANN to control the generated energy of different integrated sources In this practical experimental study, the proposed framework is to integrate ANN topology to validate the experimental capability of Field Programmable Gate Array (FPGA) technology as an innovative digital methodology to efficiently integrate PV, wave and Fuel Cells (FCs) energy generation systems in one hybrid model. This study emphasized the ability of FPGA technology in obtaining reasonable results of voltage, current and power profiles of proposed integrated energy system. The maximum percentage deviations between the experimental study with FPGA and controlling study of ANN with FPGA for the energy generation profiles of the integrated sources are expressed in Table 12. As vital operator of generation process in this study, the voltage behaviour of both experimental and controlling scenarios is shown in Fig. 14. For comprehensive illustration, current and power profiles of the integrated sources of both experimental and controlling scenarios are also shown in Fig. 14 (Talaat et al. 2022).

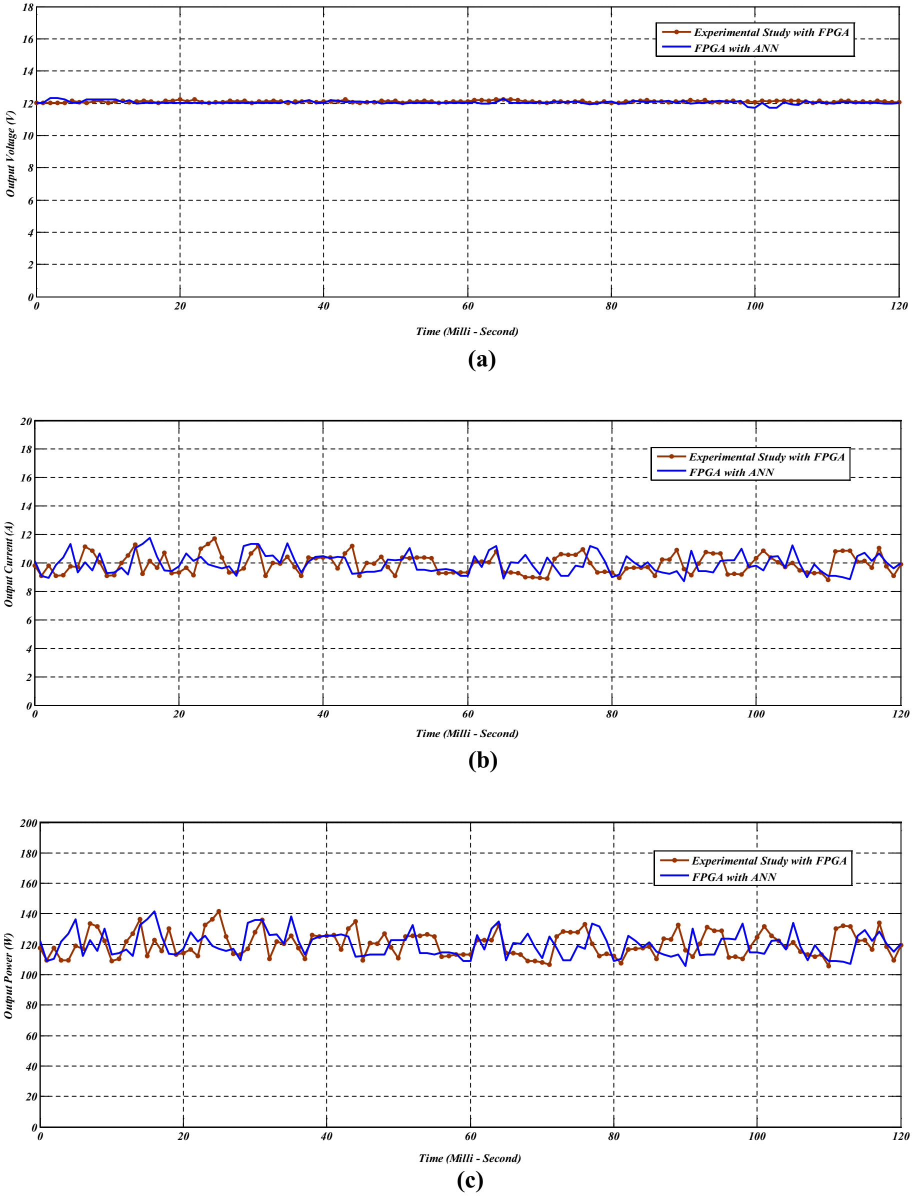


Fig. 14 Generation analysis of integrated system considering practical and controlling scenarios; **a** voltage profile, **b** current profile, c power profile

4.2 Integration of regularization methods with ANNs for analyzing complicated fields

4.2.1 General overview

There is an extreme rarity for the conducted scientific researches on the role of ANNs to improve the operational performance of regularization methods. This scarcity is due to the deep overlap of regularization methods with inverse computational considering the Bayesian Regularization Approach (BRA). Correspondingly, the integration process of ANN with the regularization methods is implicitly hidden in the studies combining numerical simulation methods together. The roles of ANNs with regularization methods are defined as follows:

- Improving the operational capability of regularization methods for precisely imitating, estimating, and optimizing the spatially scattered electromagnetic fields.
- Increasing computation accuracy with fast response for complex energy systems.
- Enabling the regularization methods to reach the optimum response with low number of iteration and reasonable convergence time.

4.2.2 Practical implementation

In this practical simulation study, the proposed framework is to integrate ANN topology with Tikhonov Regularization Approach (TRA) to numerically simulate the scattering behaviour of antenna signals due to the operational disturbances. This integrated controlling strategy of ANN with TRA provides a proper investigation of the directional disturbances of spatially scattered electromagnetic fields on the carriers of antenna signals (Sandhu et al. 2021). This strategy paves the way for normalizing optimally these scattered fields to enhance the reliability and stability of the transmission process (Sandhu et al. 2021). Furthermore, the proposed integrated controlling model improves the operation of GPOA for sampling effectively the complicated field signals by minimizing the computational error and enhancing convergence stagnation. Considering the proposed strategy, the following points can be deduced (Sandhu et al. 2021):

- The usage of ANN enables Tikhonov method to detect precisely number of samples of the linearized-optimized fields in order to construct easily the sampling matrix.
- The integration of ANN provides a magic tool for reaching the optimal distribution of scattered fields by ordering each sample according to its importance level.
- Furthermore, ANN boosts the operational performance of Tikhonov regularization method and GPOA to achieve convergence with a smaller number of generations
- Prospectively, there is a future priority to such strategies to break into scientific arena.

Schematically, the effect of integrated controlling strategy of ANN with TRA is expressed in reducing the fitness value of GPOA considering four training samples as shown in Fig. 15.

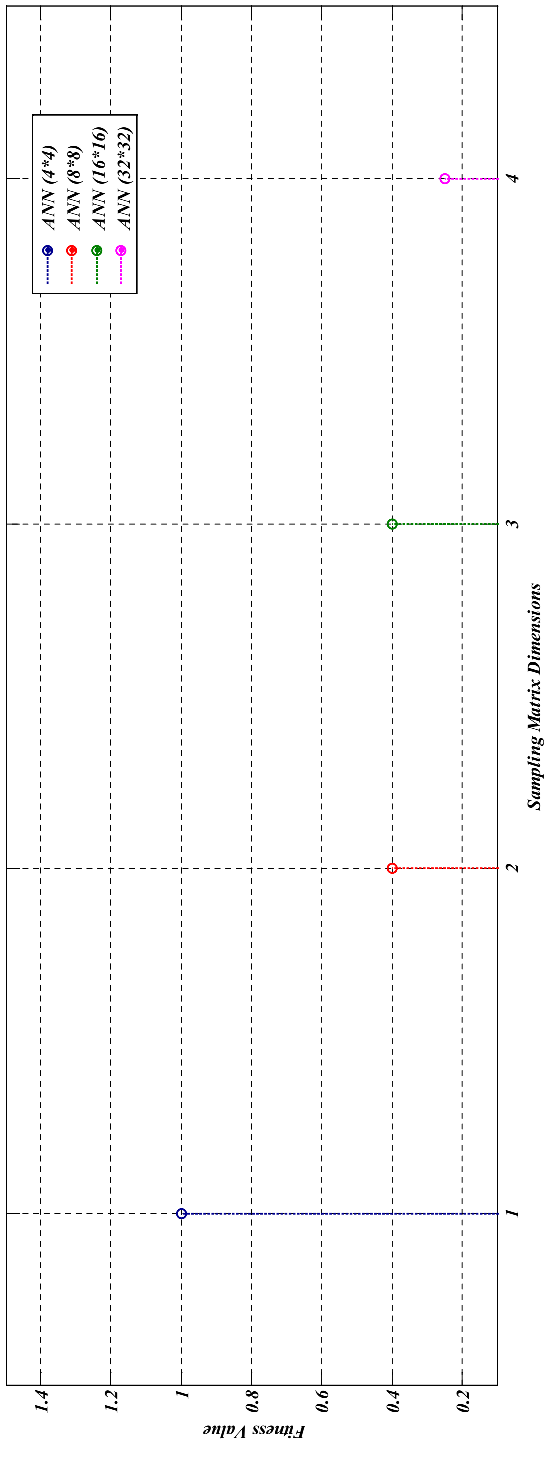


Fig. 15 Convergence of GPOA considering the TRA model trained by ANN samples

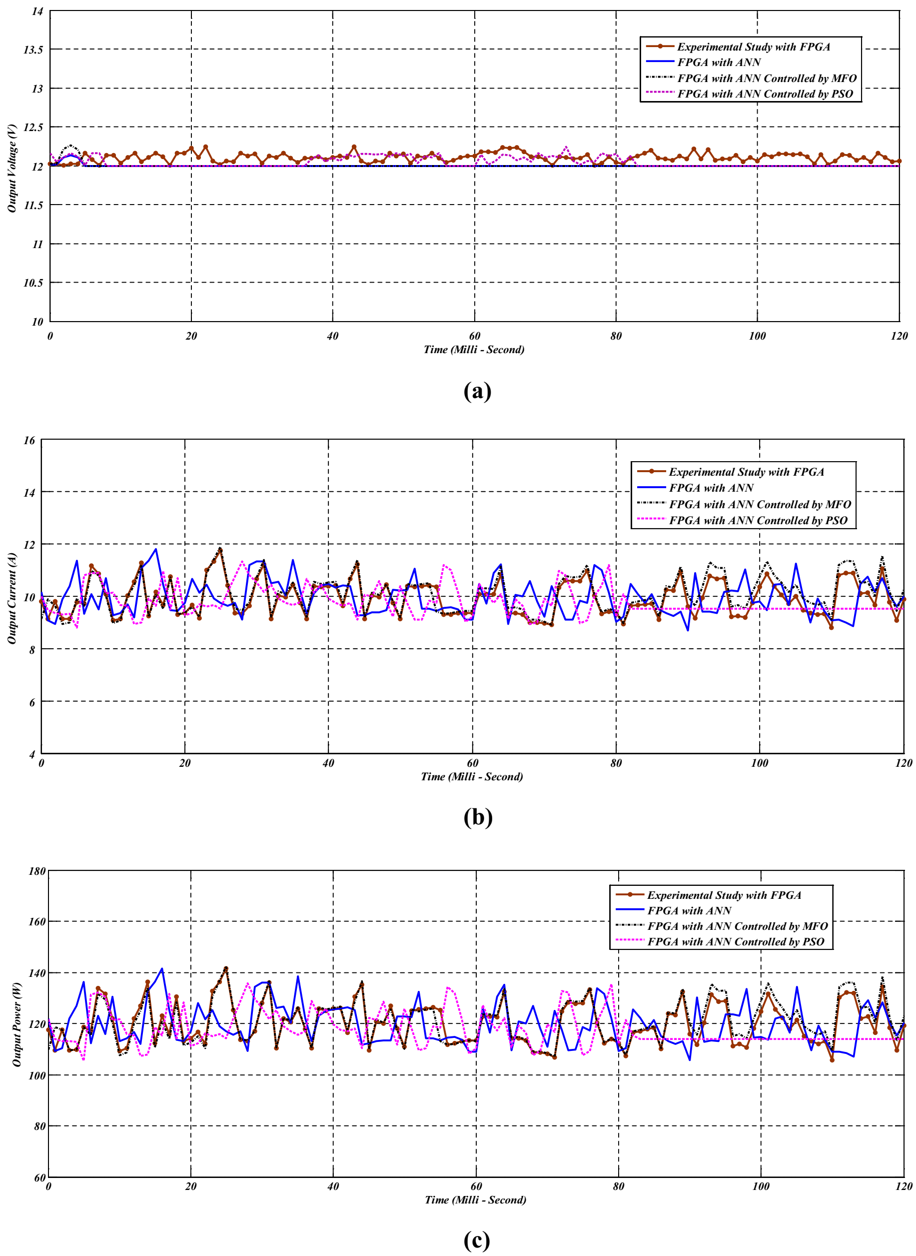


Fig. 16 Generation analysis of integrated system considering practical and controlling scenarios; **a** current profile, **b** power profile

Table 13 Practical energy systems with the hybrid integration of ANNs with inverse methods

Applied study	Simulation method	Role of ANN	References
Detect failures of induction machines	Based on the hybrid integration of ANN with the operational analysis of FEM	Identifying the affected coefficients on potential and current of asynchronous motors regarding frequency of generated magnetic fields at windings	Barzegaran et al. (2013)
Forecasting the domestic Air-Conditioning (AC) load shape regarding the big data	The hybrid model of this study is based on the integration of ANN with LMM	ANN improves the performance of LMM to process big input data of AC loads and daily temperature. It enables LMM to forecast the AC load profile based on the estimated indices for the impact of trained responses	Bourdeau et al. (2019)
Improving the operational modelling of TEG device for efficient performance	Based on the integration of ANN to enhance the analysis of CFD assisted by the FEM operational analysis	ANN enables CFD to predict power and voltage of TEG at various temperatures. It enables FEM to solve the boundary equations of estimated parameters. ANN improves the convergence time of the hybrid model of CFD assisted by FEM	Kalogirou (2001)
Forecasting the performance waveforms of solar radiation	The hybrid model of this study is based on the integration of ANN with SAA	ANN improves the operation of SAA to predict accurately the solar energy radiation per day based on the path of temperature cycling mechanism	Bahrami and Ardejani (2016), Mousavi et al. (2017)
Choosing appropriate way controls load shedding	Based on the hybrid integration of ANN with the operational analysis of MCM	Determining the optimal strategy for load shedding by calculating the optimum simulation factors of MCM regarding frequency scenarios to reach the best adaption with protection view	Thalassinakis et al. (2006)

4.3 Inverse computational methods assisted by ANNs; illustrative practical examples

The vital impact of ANNs clearly appears in improving the analysis of inverse computational methods due to the massive variety of the practical applications within electrical domains. Regarding the features of the inverse computational methods, the following points summarize the powerful effects of ANNs for enhancing the simulation process of these methods:

- Testing the effectiveness of inverse computational methods to assess their efficiency.
- Obtaining the optimal coefficients that minimize the operational errors and control the accuracy of inverse computational methods.
- Improving the computational analysis of hybrid integrated energy systems.

4.3.1 Integrated controlling strategies with energy of different integrated sources

In this practical experimental study, the proposed framework is to integrate ANN topology with MFO to optimally forecasting the controlling scenarios of FPGA as an innovative digital step to enhance the generation process of the hybrid integrated model of PV, wave and FCs. This study emphasized the ability of the integrated controlling strategy of ANN with MFO to enhance the tuning errors of ANN topology considering the training samples and stagnation. Also, this study validates the effectiveness inverse computational methods and optimization algorithms in relaxing optimally the energy generation distribution profiles. Furthermore, the strategy of ANN with MFO enhances the experimental studies considering the controlling scenarios of FPGA method. Comprehensively, the controlling strategy of ANN with Particle Swarm Optimization (PSO) is innovatively provided to show effectiveness of optimization algorithms in such studies. Voltage behaviour of both experimental and controlling scenarios is shown in Fig. 16. For comprehensive illustration, current and power profiles of integrated sources of both experimental and controlling scenarios are also shown in Fig. 16 (Talaat et al. 2022).

4.3.2 Integrated controlling strategies within energy systems

In the upcoming practical studies, the proposed frameworks that are expressed in Table 13 show the integrated controlling strategies combining ANN with the defined

Table 14 Practical energy systems integrating ANFLNs with numerical simulation methods

Applied Study	Simulation Method	Role of ANFLN	References
Diagnosing the operational faults of induction motors	The hybrid model of CRT-ANFLN is applied to improve the performance of LSQRM integrated with ANN method	Considering ANN, ANFLN enables LSQRM to improve accuracy of CRT to detect current and vibration affecting the failure of induction motors. CRT accuracy reached 91% for mechanical study and 77% for electrical one	Widodo et al. (2007), Yang et al. (2009)
Identifying the diagnostic faults of ISTEs	Model of OWAM-ANFLN is integrated with SVMM	ANFLN improves the accuracy of SVMM to determine the faults of ISTE. ANFLN—OWAM minimize faults	Salahshoor et al. (2010)
Controlling the operation of wind and DFIG systems	PSO–ANFLN is used with combined system of sensitivity method with WTM	ANFLN–PSO reduces dynamic disturbances, evaluation cost and time waste within the DFIG system	Darabian et al. (2014)
Forecasting the climax point of load demand profile	Based on ANN training, ANFLN is applied with a hybrid model of sensitivity regression with SR method	ANFLN improves stochastic regression analysis and provides with ANN a hybrid model for training data of temperature and load for predicting the highest possible demand to adapt the generation operation	Draidi and Labed (2015)

Table 15 Practical energy systems integrating CSM or FEM with optimization algorithms

Applied Study	Hybrid Model	Role of Optimization Algorithms	References
Computing and minimizing electric fields improving the accuracy of CSM within simulated HV transmission line parameters	Combining CSM separately or with FEM with one or more of the proposed optimizers algorithms: (a) GA, (b) PSO and (c) GWO	Determining numerical coefficients for optimal arrangement of fictitious charges to compute the optimal distribution of electric fields around surface of HV conductors or separators within over-head power line	Djekidel et al. (2020)
Optimizing the operational features of support insulators	The hybrid model of this study combines CSM with the innovative HIAGA methodology	Enabling CSM to optimally determine the best number of fictitious charges and their allocations. Also, detecting the optimum design of the contour points to reduce the field stresses along support insulators	Chen et al. (2008)
Investigating the optimal distribution of non–uniform electric fields for reasonable operation of HV dielectrics under the stress of CDs	The hybrid model for studying the configuration of HNP combines CSM with three different proposed optimization algorithms: (a) GA, (b) SBO and (c) WOA	Allocating optimal positions of the fictitious charges over the surface of HV needle electrode to increase accuracy of CSM. Also, enabling CSM to obtain accurate distribution of electric fields generated from CDs. Furthermore, providing CSM as a powerful imitating method	Rabah et al. (2017), Talaat et al. (2020), El-Zein et al. (2009)
Detecting the optimal design shape of the operational electrodes used in empirical studies of electrical issues	combines CSM with niching GA based on DPM to replace the conventional analytically methods	Constrained niching GA enables CSM to determine the optimal design of the operational electrodes based on the computation of potentials and fields across the optimized parameters thanks to unique features of DPM	Sareni et al. (1998)
Optimizing the structure of CRC for grading the efficiency level of UHV composite insulators	The hybrid model of this study combines FEM with PSO based on the computational simulation of ANSYS program	Obtaining optimal distribution of electric fields along CRC within UHV transmission system. Also, minimizing the excessive non–uniform fields to obtain optimum structure of CRC within UHV insulator regarding UIM criterion	Zhang et al. (2013), Doshi et al. (2011)

Table 15 (continued)

Applied Study	Hybrid Model	Role of Optimization Algorithms	References
Automatically arranging the fictitious charges and contour points along the electrode surface	The hybrid model of this study combines CSM with IOA or GA with an imaging symmetrical structure	Improving ability of optimum searching of CSM by detecting the best allocation of fictitious charges and contour points along the electrode and increasing CSM efficiency in field calculation	Nishimura and Nishimori (2005)
Imitating the performance of RPG model in the presence of DBTL to estimate the generated non-uniform fields for HV applications	The hybrid model of this study combines FEM with the following proposed optimization algorithms: (a) GA, (b) PSO and (c) MFO	Enabling FEM to overcome the complexity of accurate calculation of electric fields generated from the non-linear configuration of RPG. These optimum values are obtained at different positions of DBTL to study the tuning errors for electric field estimation using COMSOL Multiphysics program	Talaat et al. (2018)

type of inverse computational methods to simulate and validate the operation of the proposed energy system.

5 Numerical simulation methods with ANFLNs for integrated energy issues

5.1 General overview

There is a severe scarcity in practical experimental and simulation studies that are related to energy systems utilizing the ANFLNs for improving the operation of different numerical simulation methods. The reasons for this rarity can be traced back to the following points:

- The arithmetic dominance of ordinary ANN and FLCS methodologies for improving the computation of simulated problems due to their simplicity and higher accuracy.
- The permanent dependence of ANFLN on the optimization algorithms or ANN for training its parameters that increases the complexity degree of the computation.
- Despite the iconic property of global searching, ANFLN suffers from the failure of convergence regarding complex simulated problems due to low speed of processing.

5.2 Practical implementations

In the upcoming practical studies, the proposed frameworks that are expressed in Table 14 show integrated controlling strategies combining ANFLN with the defined type of numerical methods to simulate and validate the operation of the proposed energy system.

In the prospective studies, the following points may be useful to increase the computational dependence on ANFLN methodology for improving the numerical simulation analysis:

- Improving optimally the mathematical operators of ANFLN to cope with complicated electrical issues as well as obtaining the desired output response.
- The accurate analysis of the role of ANN and the different optimization algorithms to be integrated with ANFLN to test the effectiveness of this approach.

Table 16 Practical energy systems integrating hybrid simulation methods with optimizers

Applied study	Hybrid model	Role of optimization algorithms	References
The simulation of the performance of small rated DGM devices within micro-grids	The hybrid model of this study combines LMM with GA based on the utilization of GOL methodology	Enabling LMM to obtain optimal modelling of small rated DGM device. Also, identifying based on GOL, the initial iterations to obtain a reasonable performance of DGM	Long et al. (2020)
Detecting the operational features of MMS within the electrical networks of higher voltages	The hybrid model of this study combines GNM with PSO based on the utilization of DSS methodology	Obtaining fitting factors for optimal performance of MMS. Also, controlling accuracy of GNM in simulating complex non–linear fields within MMS applying DSS	Ge et al. (2020)

6 Numerical simulation methods with optimization ones for integrated systems

6.1 General overview

As the most common AI type to be used in improving the simulation analysis of different complicated electrical issues, the computerized optimization algorithms provide powerful roles in enhancing the operational performance of numerical simulation methods as follows:

- Increasing the simulation accuracy by lowering the tuning errors.
- Estimating the optimal coefficients affecting the performance of simulation methods.
- Reaching the optimum shape, size, cost, and any other performance parameters for enhancing the operational features and reliability of simulated electrical issues.

6.2 Practical implementations of integrating CSM and FEM with proposed optimizers

In the upcoming practical studies, the proposed frameworks that are expressed in Table 15 show integrated controlling strategies combining proposed optimizers with CSM or FEM to simulate and validate the operation of proposed energy system. It is worth to be mentioned that experimental and simulation studies involving CSM or FEM depend mainly on obtaining the optimum computational parameters considering the topologies of AI.

6.3 Practical examples of integrating hybrid simulation methods with optimizers

In the upcoming practical studies, the proposed frameworks that are expressed in Table 16 show integrated controlling strategies combining proposed optimizers with any defined type of numerical simulation methods except CSM and FEM.

7 Conclusions

The iconic computational analysis of AI strategies is clearly investigated in this research showing their effective capabilities for overcoming the operational obstacles of the numerical simulation methodologies regarding the energy issues. The conducted studies in this paper show the effectiveness of AI strategies as smart solutions for improving the efficiency of numerical simulation methods based on the intelligent controllability of the hybrid models integrating the AI operators with proposed numerical methods for simulating practical energy systems. Significantly, the supreme dominance of numerical methods remains the optimal solution for simulating complicated-structural energy systems. Considering the massive bifurcation of computational domains of numerical simulation methods, there are multiple studies that are reviewed in this paper showing the operational features of each category detecting the desired choice for applied case study. Furthermore, the operational hybrid models integrating numerical simulation methods with AI strategies provide a powerful way for increasing the reliability and quality of energy systems whatever the complexity degree regarding the provided practical examples. Regarding the reviewed practical examples, the unique merits of optimized numerical simulation methods are validated paving the way for several studies to highlight the significant effectiveness of this hybrid integration within different sciences in the upcoming studies. In this paper, the renewable energy systems are provided with different studies as effective practical systems for accrediting the optimal operation of the hybrid integrated simulation methods with AI strategies.

Author contributions M. Talaat: Supervision, Conceptualization, Methodology, Data curation, Resources, Writing-review & editing. M. Tayseer: Conceptualization, Methodology, Formal analysis, Software, Investigation, Data curation, Resources, Validation, Writing – original draft, Writing-review & editing. MAF: Supervision. Dongran Song: Writing-review & editing

Funding Open access funding provided by The Science, Technology & Innovation Funding Authority (STDF) in cooperation with The Egyptian Knowledge Bank (EKB).

Declarations

Competing interest The authors declare no competing interests.

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