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Optimization Strategies for Decision-Makers to Increase the Distributed Energy Resources Penetration for a Greener Future

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OPTIMIZATION STRATEGIES FOR DECISION-MAKERS TO INCREASE THE DISTRIBUTED ENERGY RESOURCES PENETRATION FOR A GREENER FUTURE

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Resumo

Integrar recursos energéticos distribuídos (REDs), especificamente geração distribuída (GD), no sistema de distribuição resulta em problemas de gestão de energia. Para cada concessionária de energia elétrica esses problemas são diferentes, são base em melhorias realizadas anteriormente nos sistemas de distribuição e em seus requisitos. Portanto, esta tese apresenta diferentes cenários de gestão de energia e soluções para uma ampla gama de problemas de otimização nos sistemas de distribuição com à integração de REDs.

Todos esses cenários consideram a alocação de RED no sistema de distribuição. Esta tese analisa as estratégias, incluindo quatro problemas de otimização de gestão de energia. O primeiro e o segundo cenários são a alocação de objetivo único e multiobjetivo de RED no sistema de distribuição. A tese contribui com os dois primeiros cenários por uma alocação e dimensionamento multiobjetivo, considerando a capacidade de hospedagem do sistema de distribuição e o RED instalado anterior (ou seja, terceiro cenário). Finalmente, o quarto cenário apresenta o despacho ótimo de REDs e microrredes para o escalonamento de usinas virtuais de energia (do inglês Virtual Power Plant - VPP).

Esses cenários incluem a alocação de GD, como células a combustível, turbinas eólicas e módulos solares, em um sistema de distribuição para orientar a gestão de energia no futuro. Nestes cenários, os algoritmos de otimização aplicados são o algoritmo aprimorado teaching-learning-based optimization (TLBO) com a apresentação de duas novas modificações e dois novos algoritmos de otimização híbrida. O primeiro e o segundo cenários usam modificações adicionais de TLBO para a colocação de DER nos problemas de objetivo único e multiobjetivo. O terceiro cenário aplica um algoritmo de otimização híbrido combinando o algoritmo TLBO e honey bee mating optimization (HBMO). O algoritmo híbrido do quarto cenário é uma combinação dos algoritmos grid search algorithm e derivative-free optimization algorithm. Os algoritmos TLBO, HBMO, grid search algorithm e derivative-free optimization algorithm foram relatados como os melhores algoritmos de otimização nesta área. Assim, esta tese, ao modificar e combinar esses algoritmos, tenta projetar um algoritmo de otimização mais adequado a cada cenário. Além disso, um sistema

de distribuição padrão IEEE, com distribuição radial de 70 barras, é usado para implementar os algoritmos de otimização propostos com base no cenário do gerenciador do sistema de potência e funções objetivo.

Os resultados mostram a importância dos algoritmos propostos para otimizar funções objetivo. A superioridade observada dos algoritmos propostos apresenta a melhor acurácia e velocidade na obtenção da solução ótima entre os demais algoritmos de otimização testados. Os algoritmos propostos são novos algoritmos de otimização que modificam a versão antiga do algoritmo de otimização ou combinam dois algoritmos de otimização. Os algoritmos propostos são novos algoritmos de otimização obtidos modificando a versão original do TLBO ou combinando dois algoritmos de otimização. A modificação do TLBO está nas fases de professor e aluno com a adição de técnicas de otimização adequadas, como técnica de aprendizagem baseada em quase oposição e método de mutação. Com soluções otimizadas, a concessionária de energia elétrica pode ter uma melhoria econômica, técnica e ambiental no sistema de potência por meio da integração dos REDs. Além disso, os prossumidores (clientes que são produtores e consumidores) podem ter todos os benefícios dos geradores renováveis.

Palavras-chave: Gerenciamento de energia; Algoritmo de otimização; Recursos energéticos distribuídos; Geração distribuída; Rede de distribuição; multiobjetivo; único objetivo.

Abstract

Integrating distributed energy resources (DERs), specifically renewable distributed generation (DG), in the distribution system leads to energy management problems. These problems for electric utilities are varied based on different former improvements in distribution systems and their requirements. Therefore, this thesis presents different energy management scenarios and solutions for covering a wide range of optimization problems in the distribution systems related to integrating DERs.

All these scenarios are in one direction under the 'placement of DER in the distribution system.' This thesis analyses the strategies, including four energy management optimization problems. The first and second scenarios are the single objective and multiobjective placement of DER in the distribution system. The thesis improves the first two scenarios by a multiobjective placement and sizing by considering the distribution system hosting capacity and the former installed DER (i.e., third scenario). Finally, the fourth scenario presents the optimal dispatching of DERs and microgrids for virtual power plant (VPP) Scheduling.

These scenarios include the allocation of DG, such as fuel cells, wind turbines, and solar cells, in a distribution system to guide future energy management. In these scenarios, the applied optimization algorithms are the improved teaching-learning-based optimization (TLBO) algorithm with presenting two new modifications and two new hybrid optimization algorithms. The first and second scenarios use further modifications of TLBO for DER placement in the single objective and multiobjective problems. The third scenario applies a hybrid optimization algorithm combining TLBO and honey bee mating optimization (HBMO) algorithm. The hybrid algorithm of the fourth scenario is a combination of grid search algorithm and derivative-free optimization algorithm. TLBO, HBMO, grid search, and derivative-free optimization algorithms have been reported as the best optimization algorithms in this area. Thus, this thesis, by modifying and combining those algorithms, tries to design a better optimization algorithm matched to each scenario. Moreover, an IEEE standard distribution system, a 70-bus radial distribution system, is used to implement the proposed optimization algorithms based on the power system manager scenario and objective functions.

The results show the importance of the proposed algorithms to optimize objective functions. The proposed algorithms observed superiority presents the best accuracy and velocity in achieving the optimal solution among the other optimization algorithms tested. The proposed algorithms are new optimization algorithms obtained by modifying the original version of the TLBO or combine two optimization algorithms. TLBO modification is in teacher and learner phases with adding the proper optimization techniques such as quasi-opposition-based learning technique and mutation method. With the best optimal solutions, the electric utility can have an economic, technical, and environmental improvement in the power system by DERs integrations. Besides, prosumers can have full benefits from renewable generators.

Keywords: Energy management; optimization algorithm; Distributed energy resources; distributed generation; distribution network; multiobjective; single objective.

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List of Abbreviations

AVR *Automatic Voltage Regulators*

DG *Distributed Generation*

DRG *Distributed Renewable Generation*

DER *Distributed energy resources*

EMS *Energy Management System*

ESS *Energy Storage System*

GA *Genetic Algorithm*

GAO *Goal attainment optimization*

HBBBC *Hybrid-Big-Bang-Big-Crunch*

OLTC *Transformer with on-load tap changers*

HBMO *Honey Bee Mating Optimization*

IEEE *Institute of Electrical and Electronics Engineers*

MOGA *Multi-Objective Genetic Algorithm*

MOPSO *Multi-Objective Particle Swarm Optimization*

MTLBO *Modified-teaching-learning-based-optimization*

MQOTLBO *Modified Quasi Oppositional Teaching-Learning-Based-Optimization*

NOx *Nitrogen oxides*

PMTLBO *Proposed modified teaching-learning-based-optimization*

PSO *Particle Swarm Optimization*

QOBL *Quasi-Opposition-Based-Learning*

SA *Simulated annealing*

SBA *Shuffled-Bat algorithm*

SKHA *Stud Krill Herd Algorithm*

Sox *Sulfur oxides*

TLBO *Teaching-Learning-Based-Optimization*

TLBO-HBMO *Hybrid optimization algorithm based on HBMO and TLBO optimization algorithms*

VPP *Virtual Power Plant*

Nomenclature list

$\mathbf{Ar}$	*Annual interest rate*
$\mathbf{a}, \mathbf{b}$	*Two real number that b is bigger than a*
$\mathbf{Capacity}$	*DER capacity [kWh]*
$\mathbf{C_{fc}}$	*Result of* $\rho + \Gamma$ *for fuel cell unit*
$\mathbf{C_{mt}}$	*Result of* $\rho + \Gamma$ *for microturbine*
$\mathbf{Capital\ cost}$	*Capital cost [$/kW]*
$\boldsymbol{\rho}$	*The DER capital cost in the lifetime*
$\mathbf{A_{ESS}}$	*The annuity factor refers to the corresponding capital investment of the* i^{th} *installed Independent ESS in the kth microgrid*
$\boldsymbol{\Gamma}$	*Total fuel cost, and operation and maintenance cost*
$\mathbf{C(p)}$	*Cost function*
$\mathbf{C_{pv}}$	*Result of* $\rho + \Gamma$ *for photovoltaic*
$\mathbf{cost_{sub}}$	*Total cost of substation*
$\mathbf{C_{wind}}$	*Result of* $\rho + \Gamma$ *for wind turbine*
$\mathbf{E_n}$	*The* n^{th} *DER emission*
$\mathbf{A_{DG}}$	*Annuity factors refer to the corresponding capital investment of the* i^{th} *installed DG in the kth microgrid*
$\mathbf{E_t}$	*The total emission of a DER type*
$\mathbf{E_{t_{fc}}}$	*The total emission fuel cell units*
$\mathbf{E_{t_{pv}}}$	*The total emission of photovoltaic*
$\mathbf{E_{t_{wind}}}$	*The total emission of wind turbines*
$\mathbf{f_1(X)}$	*The first objective function (cost)*
$\mathbf{f_2(X)}$	*The second objective function (loss)*
$\mathbf{f_3(X)}$	*The third objective function (voltage deviation)*
$\mathbf{f_4(X)}$	*The fourth objective function (emission)*
$\mathbf{F_1(X)}$	*Minimized first objective function*
$\mathbf{F_2(X)}$	*Minimized second objective function*
$\mathbf{F_3(X)}$	*Minimized third objective function*

$\mathbf{F_4(X)}$	*Minimized fourth objective function*
Fuel cost	*Fuel cost [$/kW]*
$\mathbf{f_p\ (X)}$	*p^{th} objective function*
$\mathbf{f_q(X)}$	*q^{th} objective function*
$\mathbf{f_x^{max}}$	*$f_x(X)$ Upper limit*
$\mathbf{f_x^{min}}$	*$f_x(X)$ Lower limit*
$\mathbf{f_x(X)}$	*The xth objective function*
H	*A constant between 0 and 1*
$\mathbf{I_m}$	*Actual current m^{th} branch of the distribution system*
$\mathbf{j^{rr}}$	*jumping rate*
$\mathbf{KW_{DG}^{n}}$	*The nth DERs capacity*
L	*Determined objective functions number for multiobjective problems*
LF	*Load factor*
Min	*Minimization function*
mean	*Mean function*
η	*A constant between zero and one*
$\mathbf{A_{IDG}}$	*The annuity factor refers to the corresponding capital investment of the ith installed Independent DG in the distribution system*
$\mathbf{CapIDG_i}$	*The capacity of the ith installed Independent DG in the power network (kW)*
$\mathbf{CIDG_i}$	*Cost of the ith installed Independent DG in the distribution system ($/kW)*
M	*Annual maintenance cost (subscripts refer to the corresponding plant) ($/year)*
$\mathbf{A_{IESS}}$	*The annuity factor refers to the corresponding capital investment of the ith installed Independent ESS in the distribution system*
$\mathbf{CapIESS_i}$	*The capacity of the ith installed Independent ESS in the power network (kW)*

$\mathbf{CapDG_{i,k}}$	*The capacity of the ith installed DG in the kth microgrid (kW)*
$\mathbf{CDG_{i,k}}$	*Cost of the ith installed DG in the kth microgrid ($/kW)*
$\mathbf{CIESS_{i}}$	*Cost of the ith installed Independent ESS in the power network ($/kW)*
$\mathbf{CESS_{i,k}}$	*Cost of the i^{th}installed Independent ESS in the kth microgrid ($/kW)*
$\mathbf{OutDG_{i,j,k}}$	*The output of ith DG in the kth microgrid at the jth period (kW)*
$\mathbf{hIESS_{u,i}}$	*Maximum charge rate for i^{th} ESS*
$\mathbf{hIESS_{l,i}}$	*Maximum discharge rate for i^{th} ESS*
$\mathbf{McIESS_{i,j}}$	*The maintenance cost of ith independent ESS in the power network at the jth period ($/kWh)*
$\mathbf{McESS_{i,j,k}}$	*The maintenance cost of ith ESS in the kth microgrid at the jth period ($/kWh)*
$\mathbf{VESS_{i,j,k}}$	*Electricity stored in the ith unit of the kth microgrid in period j (kWh)*
$\mathbf{OutIDG_{i,j}}$	*The output of ith independent DG in the power network at the jth period (kW)*
$\mathbf{RDG_{u,i,k}}$	*Ramp up the limit for i^{th} independent DG*
$\mathbf{RIDG_{u,i}}$	*Ramp up the limit for i^{th} independent DG*
$\mathbf{PIESS_{i}}(\boldsymbol{\gamma})$	*Fixed cost for independent ESS components, as a function of the number of sites (k) and the distance between sites (γ)*
$\mathbf{rIESS_{i,j}}$	*Buyback price for exported electricity to the ith independent ESS in period j*
$\mathbf{PIESS_{i,j}}$	*Price for electricity imported from the ith independent ESS in period j*
$\mathbf{IIESS_{i,j}}$	*Electricity imported from the ith independent ESS in period j*
$\mathbf{PIDG_{i}}(\boldsymbol{\gamma})$	*Fixed cost for independent DG components, as a function of the number of sites (k) and the distance between sites (γ)*
$\mathbf{rIDG_{i,j}}$	*Buyback price for exported electricity to the ith independent DG in period j*

$\mathbf{EIDG_{i,j}}$	*Electricity exported to the ith independent DG in period j*
$\mathbf{PIDG_{i,j}}$	*Price for electricity imported from the ith independent DG in period j*
$\mathbf{IIDG_{i,j}}$	*Electricity imported from the ith independent DG in period j*
$\mathbf{P_{sub}}$	*Substation power rating*
$\mathbf{N_{bus}}$	*Maximum network-bus number*
$\mathbf{N_{DG}}$	*Specified DERs number*
nDG	*Maximum DERs number*
$\mathbf{N_{fc}}$	*Fuel cell number*
Life time	*lifetime [h]*
$\mathbf{N_{nb}}$	*Maximum network branches number*
$\mathbf{N_{mt}}$	*Microturbine number*
$\mathbf{N_{lt}}$	*DERs lifetime*
$\mathbf{N_{pv}}$	*Photovoltaic number*
$\mathbf{N_{wind}}$	*Wind turbine number*
O & M cost	*DERs operation and maintenance cost [$/kW]*
p	*Active power*
$\mathbf{P_{fc}}$	*The fuel cell unit's generated power*
$\mathbf{P_{load}}$	*Total load power*
$\mathbf{P_{mt}}$	*The microturbine's generated power*
$\mathbf{P_{n}}$	*The nth generator's electrical output*
$\mathbf{P_{pv}}$	*The photovoltaic unit's generated power*
$\mathbf{P_{sub}}$	*Injected active power of substation*
$\mathbf{P_{wind}}$	*The wind turbine's generated power*
$\mathbf{Q_{sub}}$	*Substation injected power cost [$/kW]*
$\mathbf{R_{m}}$	*The mth resistance network-branch*
var	*Variance*
$\mathbf{V_{m}}$	*The mth network-bus voltage magnitude*
$\mathbf{V_{max}}$	*Upper voltage restrictions*
$\mathbf{V_{min}}$	*Lower voltage restrictions*
$\mathbf{V_{nom}}$	*Network-bus nominal voltage*

$\mathbf{V_r}$	*Network-bus voltage magnitude*
$\mathbf{X}$	*DER's location and power vector*
$\mathbf{X_{new}}$	*New optimization-population member (new learner)*
$\mathbf{X_{old}}$	*Old optimization-population member (old learner)*
$\mathbf{X_r^{diff}}$	*The contrast between the teacher's learning level and the mean of the class at any iteration*
$\mathbf{X_{r+1}^{New}}$	*New teacher's learning level in iteration r+1*
$\mathbf{X_r^{Old}}$	*Teacher's learning level in iteration r*
$\mathbf{X_r}$	*Matrix of location (discrete numbers) and size (continues numbers) of DG units*
$\mathbf{X_x}$	*Learner x (feasible solution x)*
$\mathbf{X_z}$	*Learner z (feasible solution z)*
$\mathbf{X_K^{sa,v}}$	*SA vector (with K vector component for v^{th} member of population)*
$\mathbf{X_K^v}$	*Feasible solution vector (with K vector component for vth member of population)*
$\mathbf{X_K^{new}}$	*New generated member of the population*
$\mathbf{X_{K+1}^{new}}$	*Equal to X_K^{new} or X_K^v based on mentioned conditions*
$\mathbf{Z}$	*Any real number between [a,b]*
$\mathbf{z^*}$	*Opposite number*
$\mathbf{z_d^{qo}}$	*Quasi opposite point*
$\mathbf{z_d^*}$	*Opposite point z^**
$\mathbf{z_{qo}}$	*Quasi opposite number*
$\boldsymbol{\alpha}$	*Any value for which the normal distribution function is required*
$\boldsymbol{\alpha_1}$	*Minimum of membership function of ith feasible solution*
$\boldsymbol{\alpha_2}$	*Minimum of membership function of the new feasible solution*
$\Delta\mathbf{t}$	*Time step [year]*
$\boldsymbol{\mu_x^f}(\mathbf{X})$	*Membership function*
rand	*A random number in [0, 1]*
$\boldsymbol{\alpha_n}, \boldsymbol{\beta_n}, \boldsymbol{\gamma_n}, \boldsymbol{\lambda_n}, \boldsymbol{\xi_n}$	*The nth DER emission characteristics coefficient*

$\mathbf{OutESS_{i,j,k}}$	*The output of ith ESS in the kth microgrid at the jth period (kW)*
$\mathbf{VIESS_{i,j}}$	*Electricity stored in the ith unit in period j (kWh)*
$\mathbf{OutIESS_{i,j}}$	*The output of ith independent ESS in the power network at the jth period (kW)*
$\mathbf{McIDG_{i,j}}$	*The maintenance cost of ith independent DG in the power network at the jth period ($/kWh)*
$\mathbf{W_j}$	*Weighting for period j (the reflection of the number of days of this 'type' per year)*
$\mathbf{McDG_{i,j,k}}$	*The maintenance cost of ith DG in the kth microgrid at the jth period ($/kWh)*
$\mathbf{CapESS_{i,k}}$	*The capacity of the ith installed ESS in the kth microgrid (kW)*
$\mathbf{RDG_{l,i,k}}$	*Ramp down the limit for i^{th} DG of kth microgrid*
$\mathbf{hESS_{l,i,k}}$	*Maximum discharge rate for i^{th} ESS of kth microgrid*
$\mathbf{RIDG_{l,i}}$	*Ramp down the limit for i^{th} independent DG*
$\mathbf{V_b}$	*Voltage magnitude at bus b*
$\mathbf{EIESS_{i,j}}$	*Electricity exported to the ith independent ESS in period j*
$\mathbf{r_{j,k}}$	*Buyback price for exported electricity to the kth microgrid in period j*
$\mathbf{E_{j,k}}$	*Electricity exported to the kth microgrid in period j*
$\mathbf{P_{j,k}}$	*Price for electricity imported from the kth microgrid in period j*
$\mathbf{I_{j,k}}$	*Electricity imported from the kth microgrid in period j*
$\mathbf{Pmicrogrid_k(\gamma)}$	*Fixed cost for microgrid components, as a function of the number of sites (k) and the distance between sites (γ)*
$\mathbf{hESS_{u,i,k}}$	*Maximum charge rate for i^{th} ESS of kth microgrid*
$\mathbf{P_{sub}}$	*Substation power rating*

Content

1 INTRODUCTION

A greener future with superior economic benefits for generating electric energy is the significant general effort of energy scholars and many governments worldwide. Typically, to have a greener system, renewable energy resources for developing electrical power are the best replacement for fossil fuel. Besides, to have superior economic benefits, the distributed generation (DG) or distributed energy resource (DER) concept is a conventional way of applying renewable energy resources to a distribution system. Moreover, some technical issues such as degradation of the old fashion system, and power quality issues such as conductor loss and voltage stability make the DER integration a critical optimization problem. Thus, electric utilities need some optimization processes to integrate DERs into the distribution system efficiently. Optimization processes try to determine the optimal solutions by optimization algorithms that are approaches for the distribution system decision-makers. Therefore, the next generations can have a greener future with superior economic benefits using optimization processes [1,2].

We can mention that the DER placement (i.e., the subject of this thesis) is mostly related to the operation of the power system (i.e., dispatch problem) rather than planning of distribution system (i.e., energy management problem). The concerns in DER placement are the accuracy and calculation time of optimization algorithms that are useful in the operation of the system. In some countries such as Brazil, these issues mostly considered in the transmission system, not distribution system, because the electric utilities mostly cannot generate electricity. But with increasing DER integration considering these issues will be useful for these countries in future. On the other hand, the time and accuracy of optimization algorithms is not a significant issue in energy management problems because the optimum solution is more important to install the DER. Also, these issues of optimization algorithms are vital in the regulatory sector to audit the electricity market in other types of energy management problems. It means that the optimization algorithms (i.e., part of this study) in energy management problems are useful before the regulation as a tool to help the audits.

Recently, optimization processes have suggested energy management approaches for developing and improving power systems. The authors of [3] have reviewed the energy management approaches for integrating DERs into the distribution system. They have reported that the reviewed papers' common conclusion is the primary role of optimization algorithms in optimal DERs integration. [4] and [5] have discussed the scheduling and dispatching models for integrating DERs by using two heuristic optimization algorithms. These papers' typical result is that the heuristic optimization algorithms are better than classical mathematical optimization algorithms for these specific optimization problems due to the importance of calculation velocity and accuracy. The traditional mathematical optimization algorithms are more accurate but slow [6]. Analysis of the literature survey shows many heuristic optimization algorithms, such as group search optimization (GSO) [7], particle swarm optimization (PSO) [8], honey bee mating optimization (HBMO) [9], and hybrid optimization [10] algorithms for energy management problems. These articles have tried to find the best optimization algorithm for a specific energy management scenario, such as DERs placement and sizing in the distribution system. A portfolio of reviewed papers for DER placement is shown in Table 1. This table compares the objective functions and modes, optimization methods, and variables in recently published papers.

Table 1 Reviewed papers portfolio for DER integration in the distribution system

Ref	Objective functions	Planning variables			Reported optimization algorithm as the best one among the tested ones	Objective-function mode
		sizing	siting	dispatching		
[1]	Minimizing costs, losses, and voltage deviation	Yes	Yes	No	Honey Bee Mating Optimization Algorithm	Multi
[2]	Minimizing cost and energy loss	No	Yes	No	Modified Genetic Algorithm	Multi
[4]	Minimizing voltage deviation	No	Yes	No	Particle Swarm Optimization	Single
[5]	Minimizing cost	No	No	Yes	Particle Swarm Optimization	Single
[6]	Minimizing loss	No	Yes	No	Hybrid Algorithm	Single
[7]	Minimizing loss	Yes	Yes	Yes	Group Search Optimization Algorithm	Single

[8]	Maximizing fault detection function	Yes	No	Yes	Teaching Learning-Based Optimization Algorithm	Single
[9]	Minimizing costs, losses, voltage deviation, and emission	Yes	Yes	No	Honey Bee Mating Optimization Algorithm	Multi
[10]	Minimizing costs, and emission	Yes	No	Yes	A trip-ahead optimization algorithm	Single
[11]	Minimizing costs, and emission	No	No	Yes	Teaching Learning-Based Optimization Algorithm	Multi
[27]	Minimizing costs, losses, and voltage deviation	Yes	Yes	No	Teaching Learning-Based Optimization Algorithm	Single

Research papers have considered various objective functions for DERs placement and sizing in the distribution system as an energy management scenario. Articles [11–14] have formulated cost, loss, voltage deviation, and emission as the objective functions. This thesis has considered all of these objective functions. Authors of [15–18] have assumed the single-objective concept. For improving these papers, this thesis has suggested the multiobjective idea for this optimization problem.

The application of DER placement and sizing depends on the operation model and ownership of DER in different power system scenarios [19]. Some scholars may state that with attention to installing DER in every DER owner's houses and places, they can use all network-buses to connect DER. Therefore, why do DER owners need DER placement in case that they have specific locations?

The state of DER owners can use every network-bus for connecting DER is a true statement. And DER placement is meaningful for other types of DER ownership and systems. Decision-makers mostly decide based on the aims of the DER owner, who can be a utility, customer, or third-party investor. The DER ownership type is the Customer-Centric [20] and the Utility-Centric [21], Third-Part-Centric [22], or a combination of all [23] that these types can change the power system scenario. An example is when the utility owns the DER. In this scenario, after using the DER placement concept and installing DER in the optimum place with the optimum size, the utility can sell or lease DER to the customers or use DER to generate electricity,

which is the benefit of DER placement for the electric utility. The other situation is when third-parties (i.e., non-utilities companies) want to invest and to operate their DER units as the dispatchable and synchronous units in the network. The third-parties objective may be providing services to the distribution system and customers. They may derive value by selling aggregated services to utilities or offering those services into wholesale markets. In this case, using DER placement, the best place to optimum DER owners' objectives would be the best option. Another issue is that the utility can share the benefits of installing DER units in the stock market's best places. In this case, everybody can participate based on their investment cost. Therefore, DER placement is a vital concept in specific scenarios [24].

This thesis presents different scenarios based on the distribution system requirements, operation model, and DER ownership. These scenarios are shown in Table 2. This table shows who can benefit from the proposed scenarios.

Table 2 The proposed scenarios of this study

Scenario number	Scenario title	Suitable for
1	optimal single objective placement of DER on a distribution system	Utility, third-party
2	optimal multiobjective placement and sizing of DER in a distribution system	Utility, third-party
3	optimal multiobjective placement and sizing of DER considering the distribution system hosting capacity and former installed DER	Utility, third-party
4	optimal dispatching of DERs and microgrids for Virtual Power Plant (VPP) Scheduling	Utility- third-party, customer

For achieving the perfect optimal solutions to these scenarios, the challenges are faced by the energy managers as follows:

The first challenge is to match the DERs placement problem to the whole power system [25]. There is not the same power system with the same electricity market tariffs and standards in all countries. Moreover, the different DERs ownership and application can change the optimization problem. Therefore, scholars and researchers are interested in making this emerging challenge more realistic to the power system [26].

The other challenge is the existence of DERs in a non-orderly fashion in the power systems [27]. In most power systems mentioned, degradation in operations and power

quality are reported. Therefore, scientists have been motivated to find the optimal solution for this anarchy problem (i.e., nonlinear, non-convex, and complex problem) of DERs. Additionally, scholars have been interested in more accurate and fast optimization algorithms to benefit the electricity market [28].

Furthermore, even though DERs integration in the distribution system has many advantages [29], a few studies have considered all the aspects of this optimization problem, such as evaluating the distribution system hosting capacity and installed DERs in the system. Additionally, the decision-making process of DER placement needs a method to avoid the human decision-making interface. Some plans only focus on the DER's sizing without considering the best installation location, such as [30]. Therefore, the need to find a multiobjective optimization algorithm for DER sizing and placement with having great accuracy in solving and incredible calculation velocity and giving a decision-making tool makes this research more reasonable.

This thesis prepared four energy management scenarios for integrating DERs in a distribution system to cover all these challenges. This thesis presents the best optimization algorithms and optimal solutions for each scenario, specifically.

1.1 Analyzed Scenarios

1.1.1 Optimal Single Objective Placement of DER on A Distribution System (First scenario)

Utilizing DER may have some advantages for the distribution system, such as improving power quality issues if they generate electricity in a suitable place with the right capacity. The scenario of finding the optimal location in the distribution system for the installation of DER is an optimization problem. The DER ownership type can be Utility-Centric, Third-Part-Centric, or a combination of them in this scenario. The most important single objective for these two owners of DER is the cost of generating electricity. In some cases, the voltage deviation or energy losses is reported as the single objective that is significant for them [15,24]. Therefore, we analyze these objectives in this scenario.

In this regard, this study in the first scenario presents a single-objective modified teaching-learning-based-optimization (TLBO) algorithm for the siting and sizing of DERs in a distribution network. This thesis considers three objective functions for this scenario: minimizing power generating cost and the distribution network voltage deviation and losses. Micro-turbines and fuel cell units are two DER types in this scenario. We have modified the original TLBO algorithm in the learning and teaching phases for improving convergence accuracy and velocity. Lastly, we have executed the improved optimization algorithm on a distribution test network compared to other optimization algorithms. The main advantage of the enhanced optimization method is related to the velocity and accuracy of the calculation.

1.1.2 Optimal Multiobjective Placement and Sizing of DER in A Distribution System (second scenario)

This scenario improves the first scenario by considering the DER placement as a multiobjective optimization problem. This improvement makes DER placement suitable for electric utilities that have several objective functions that these objectives may affect each other [31]. If the electric utility has a single-objective, the first scenario's presented algorithm is the best one. Like the first scenario, the second scenario's DER ownership type is Utility-Centric, Third-Part-Centric, or a combination. The most crucial objective function for these DER owners is the cost of generating electricity and the other objectives that may affect it, such as the voltage deviation or energy losses for them. Also, in some cases, the emission of greenhouse gases is reported as the significant objective function. Therefore, we present a multiobjective function of the mentioned objectives in this scenario.

This thesis in the second scenario presents a new multiobjective improved optimization algorithm for the DERs placement on a distribution test system. In this regard, the modified optimization algorithm combines the quasi-oppositional-simulated-annealing (QOSA) and TLBO algorithms. This scenario considers fuel cells, photovoltaics, and wind turbines as DERs. Moreover, the objective functions are the same as the first scenario's three objective functions, plus minimizing greenhouse gas emissions in the distribution system. We have designed the proposed hybrid

algorithm to improve the accuracy of this specific optimization problem. Also, we applied a quasi-opposition-based-learning (QOBL) technique to enhance the convergence velocity.

Additionally, we have implemented the compromise solutions method coupled with the fuzzy clustering technique because objective functions diversity. Through the proposed approach, the decision-maker has the option of selecting the best Pareto optimal solution. We have executed the suggested optimization method on a radial distribution test network and compare it with other optimization algorithms. We have proved the importance and superiority of the proposed optimization method in achieving the optimal solution of the multiobjective DERs placement in a distribution system.

1.1.3 Optimal Multiobjective Placement and Sizing of DER Considering the Distribution System Hosting Capacity and Former Installed DER (third scenario)

Another challenge for integrating DERs in the distribution system is expanding the system hosting capacity constraints[32]. Hosting capacity is essential for the electric utilities with some installed DERs in the distribution system, and continuing adoption of DERs may cause problems for the grid. We have tried to cover this challenge in the third scenario of this thesis. Like the last two scenarios, the DER ownership type in the third scenario is Utility-Centric, Third-Part-Centric, or a combination of them. The most vital objective function for these DER owners is the cost of generating electricity and the other objectives that may affect it, such as the voltage deviation or energy losses for them.

The third scenario presents a new hybrid optimization algorithm combination of TLBO and honey-bee-mating-optimization (HBMO) algorithms for optimal DERs placement. We have considered fuel cell units as DERs, and the objective functions are the same as the first scenario. We have adopted the IEEE 70-bus test system's proposed technique and compare its performance with those of other evolutionary algorithms. We have shown the computational speed and accuracy of the proposed optimization method as its superiority.

1.1.4 Optimal Dispatching of DERs and Microgrids for Virtual Power Plant (VPP) Scheduling (fourth scenario)

The last but not least scenario is DER integration management. This scenario considers that all buses of the distribution system contain DERs. The DER ownership can be all types, including Customer-Centric, Utility-Centric, Third-Part-Centric, and a combination of all. The most crucial objective function for all types of DER owners is primarily the cost of generating electricity or the emission of greenhouse gases. The optimization problem is finding the optimal dispatch of DERs, energy storage systems (ESSs), and microgrids generations for the virtual power plant (VPP) schedule[33].

In this regard, this thesis presents a new hybrid optimization algorithm for cost and emission minimization of a VPP to design and commitments of DER, microgrid, and ESS. We have accurately illustrated the VPP schedule to operate optimally. We have implemented the proposed model to a set of United States commercial load profiles. We have determined the feasible solution concerning variation in energy price. We have shown the best reasonable optimal solutions for VPP decision-makers. Comparing the proposed optimization algorithm with Genetic, PSO, derivative free, and grid search algorithms proves its superiority in accuracy and calculation velocity, making it essential for electrical marketing.

1.2 Methodology (overview)

According to economic, power quality, and pollution issues, power systems need to change the power generation structure from traditional central large power plants to small distributed generation (DG). Among the central power generation difficulties, we can mention a large staff's requirements, economic investment and space, and transmission lines problems, such as high cost of acquisition, operation, and maintenance. The main problem of central power generation is the high annual losses of transmission line conductors due to the considerable distance between the power plants and loads. In current distribution networks, especially with the growing trend of privatization and the competition of the electricity market, electric utility companies'

main goal is to decrease the cost of exploiting, maintaining, and building their network and simultaneously increasing the network and subscribers reliability [7,34].

One of the most effective methods for responding to load growth and reliability is DER integration. In this regard, small power generators, up to 10-megawatt electricity generators, are located near the load. These generators are conventionally photovoltaic units, wind turbines, diesel generators, fuel cells, micro-turbines, or any combination [35]. The main advantages of DERs integration are decreasing losses, voltage deviation, greenhouse gas emissions and costs of generating electricity, improving voltage profile, and power quality factors of the power system. Moreover, DER integration leads to access to new energies (positive environmental effects), privatization by converting large investors to small investors, increasing the power system flexibility for future developments, etc. [36]. For achieving the above objectives, we have considered different scenarios in this thesis.

The thesis methodology involves preparing, designing, and analyzing the best optimization algorithms to solve the energy management scenarios of integrating DERs in a distribution system. However, according to the No Free Lunch Theorem [37], we cannot introduce an optimization algorithm for all optimization problems; we thus need to find the best optimization algorithm for each. Hence, we tried to find the best methodology (i.e., the best optimization algorithm) for solving each scenario. We proved the proposed optimization algorithms' ability and effectiveness by comparing the algorithms with related famous optimization algorithms. Also, we tried to provide a more applicable methodology for power utilities to benefit from that.

1.3 Objectives

Optimizing the power quality issues and cost of generating electricity in a distribution system are the main objectives of this thesis. The aim is to find the best optimal solution for using DERs based on the proposed scenario in the distribution system to optimize objective functions with high accuracy and high computational speed. The objective functions include minimizing production costs, losses, emission of greenhouse gases, and voltage deviations. Other research goals are making new

optimization algorithms meet these aims and providing optimal solutions in the dominant aspect of multiobjective problems.

1.4 Contribution and structure

We summarize the main contribution of this thesis as follows:

- This thesis presents the new optimization algorithms for four designed scenarios that have superiority in accuracy and calculation velocity among tested optimization algorithms.

Also, the miner contributions of this thesis are as follows:

- This thesis presents four energy management scenarios to cover a wide range of the possibilities of DER integration.
- This thesis compares the suggested optimization algorithms results with the reported optimization algorithms as the best ones.
- This thesis analyses the multiobjective concept, hosting capacity of the distribution system, and the former installed DERs for DERs placement in the distribution system.
- This thesis presents the best VPP schedule for the optimal dispatch of DERs generations.
- The proposed methodology of this thesis considers the interdependence adequacy for DERs integration.

The thesis structure is as follows:

After the first chapter, in which we have presented an introduction to the interests and reasons for research on the subject and a literature review, we introduce the problem formulation and its constraints, objective functions, and limitations in the second chapter. The third chapter expresses models, concepts, and definitions of instruments used in the scenarios. Chapter 4 mentions the proposed optimization algorithms and techniques. Chapter 5 and 6 are related to simulation results of four proposed energy management scenarios, and finally, we have presented a prospect for future research and general conclusions in Chapter 7.

2 PROBLEM FORMULATION

The proposed energy management scenarios are optimization problems. For formulating each optimization problem, we have needed to determine the objective functions and constraints of the problem. This chapter computes and defines the objective functions, controls, and variables of each scenario.

2.1 The first scenario formulation

The first scenario is single objective DERs placement on a distribution system. This scenario aims to determine the DERs best location and generate size to minimize the objective function. We have defined three objective-functions that we have used as a single-objective function in the proposed optimization algorithm. Moreover, the constraints for considering Micro-turbines and fuel cell units as two DER types in this scenario are defines. It is noteworthy to keep in mind that the DER ownership type is not Customer-Centric in this scenario. We have considered the Customer-Centric DER ownership type in the fourth scenario.

2.1.1 Objective functions

- Total generation cost objective function

We have considered the power generation cost as the first objective function of this scenario as follows [24]:

$$C(p) = \rho + \Gamma \times p \tag{1}$$

$$\rho = \frac{Capacity(KWh) \times Capital\ cost\ \left({}^{\$}/_{KW}\right) \times Ar}{Life\ time \times LF \times 365 \times 24} \tag{2}$$

$$\Gamma = Fuel\ cost\ \left({}^{\$}/_{KW\ h}\right) + O\ \&\ M\ cost\ \left({}^{\$}/_{KW\ h}\right) \tag{3}$$

$$f_1(X) = \sum_{i=1}^{N_{mt}} C_{mt}(P_{mt}) + \sum_{i=1}^{N_{fc}} C_{fc}(P_{fc}) + cost_{sub} \tag{4}$$

$$cost_{sub} = Q_{sub} + P_{sub} \tag{5}$$

$$F_1(X) = \min\,[f_1(x)] \tag{6}$$

Where Ar, O & $M\ cost$ and Lf represent the rate of annual interest, maintenance cost of DGs and the load factor and the operation, respectively. Also, N_{mt}, N_{fc}, P_{mt}, and P_{fc} represent the numbers and generated power of micro-turbine units, and fuel cell units, respectively. Q_{sub} and P_{sub} represent the installation cost and power rating of the substation, respectively.

- Voltage deviation objective function

We have defined the bus voltage deviation of the distribution system as the second objective function of this scenario as follows:

$$f_2(X) = \sum_{m=1}^{N_{bus}} \frac{|V_{nom} - V_r|}{V_{nom}} \rightarrow F_2(X) = \min(f_2(X)) \tag{7}$$

Where V_{nom} and V_r represent nominal voltage and real voltage of the ith bus, respectively. N_{bus} is the total number of buses and $f_2(X)$ represents the second objective function.

- Power losses objective function

We have defined the third objective function as the real power loss, which should be minimized as follows:

$$f_3(X) = \sum_{a=1}^{N_{lt}} \sum_{b=1}^{N_{nb}} (R_i \times |I_i|^2 \times \Delta t) \rightarrow F_3(X) = \min(f_3(X)) \tag{8}$$

Where $\boldsymbol{N_{lt}}$ and $\boldsymbol{N_{nb}}$ are lifetime of DGs and the number of the branches, respectively. $\boldsymbol{I_i}$ and $\boldsymbol{R_i}$ are actual current and resistance of the ith branch and $\boldsymbol{\Delta t}$ is time step.

2.1.2 Constraints (problem restrictions)

- Limitation of the voltage

This thesis considers the voltage limitation of the distribution system as a constraint that should be kept as follows:

$$V_{min} \leq |V_m| \leq V_{max} \tag{9}$$

- DER size

The second constraint that we consider for this scenario is the limitation for the maximum allowable investment of DERs that leads to selecting the total capacity of DERs as follows:

$$\sum_{n=1}^{n_{DG}} KW_{DG}^{n} \leq \eta P_{load} \tag{10}$$

Where P_{load} represents the total load power and KW_{DG}^{n} is the capacity of the nth DG. η is a constant (i.e., $0 < \eta < 1$).

2.2 The second scenario formulation

Optimal multiobjective DERs placement and sizing is the second energy management scenario of this thesis. We have considered the multiobjective concept to obtain the effects of the objective functions because usually, the objective functions in placement optimization problems have conflict. This scenario finds photovoltaic units, wind turbines, and fuel cell units as the DERs. The electric utility (i.e., the decision-maker) determines the objective functions based on the power system's requirements and customers. In this regard, we have considered the most critical objective functions for electrical utilities, including minimization of cost, loss, voltage deviation, and greenhouse gas emission. The thesis aim for this scenario is to determine the optimal DERs size and location in somehow the objective functions are minimized.

2.2.1 Objective functions

- Total generation cost objective-function

The cost objective-function is the same as the first scenario, but the DERs types are changed in this scenario, so the cost objective-function is changed as following [38]:

$$C(p) = \rho + \Gamma \times p \tag{11}$$

Where ρ and Γ are defined as:

$$\rho = \frac{Capacity(KWh) \times Capital\ cost\ \left({}^{\$}/_{KW}\right) \times Ar}{Life\ time \times LF \times 365 \times 24} \tag{12}$$

$$\Gamma = Fuel\ cost\ \left({}^{\$}/_{KW\ h}\right) + O\ \&\ M\ cost\ \left({}^{\$}/_{KW\ h}\right) \tag{13}$$

$$f_1(X) = \sum_{i=1}^{N_{pv}} C_{pv}(P_{pv}) + \sum_{j=1}^{N_{fc}} C_{fc}(P_{fc}) + \sum_{k=1}^{N_{wind}} C_{wind}(P_{wind}) + cost_{sub} \tag{14}$$

$$cost_{sub} = Q_{sub} \times P_{sub} \tag{15}$$

$$F_1(X) = \min\ [f_1(X)] \tag{16}$$

Where N_{pv}, N_{fc}, N_{wind}, P_{pv}, P_{fc}, and P_{wind} represent the numbers and generated power of photovoltaic units, fuel cell units, and wind units, respectively. Q_{sub} and P_{sub} represent the installation cost and power rating of the substation, respectively. We will define X as the vector of the fuel cell, wind, and photovoltaic units' location and power in chapter 3. The cost objective function is the first objective of this scenario (i.e., $f_1(X)$) that should be minimized by the proposed optimization algorithm [9].

- Voltage deviation objective function

The second objective function for multiobjective DERs placement in the distribution system is the power electrical distribution system's bus voltage deviation. The formulation is the same as the dual objective function of the first scenario (i.e., Eq. (7)) [9].

- Power losses objective function

The real power loss energy (i.e., $f_3(X)$) is the third objective function in DERs placement and sizing in the electrical power distribution system. The formulation is the loss objective function of the first scenario (i.e., Eq. (8)) [39,40].

- Emission objective function

The fourth objective function is the greenhouse gas emission. Greenhouse gases contain Sulphur oxides (i.e., SOx) and nitrogen oxides (i.e., NOx) emitted from fossil-fueled power generators. The greenhouse gasses emission objective function can be calculated as follows:

$$E_t = \sum_{n=1}^{nDG} E_n(P_n) = \sum_{n=1}^{nDG} (\alpha_n {P_n}^2 + \beta_n P_n + \gamma_n + \xi_n \exp(9\lambda_n P_n)) \quad (17)$$

$$f_4(X) = E_{t_{fc}} + E_{t_{wind}} + E_{t_{pv}} \quad (18)$$

$$F_4(X) = min\ (f_4(X)) \quad (19)$$

Where $\xi_n, \gamma_n, \beta_n, \alpha_n$ are the nth generator emission characteristics coefficients. P_n and nDG are the electrical output of the nth generator and the number of generators, respectively. $f_4(X)$ is the emission objective function that should be considered in the proposed optimization algorithm's minimization process [41].

2.2.2 Constraints

- Limitation of voltage

Similar to the first scenario, we should keep the permissible voltage limits for the network. We can use Eq. (9) for this constraint.

- Number of DERs

Ideally speaking, the distribution system losses could be zero if the local DERs generate the electricity loads' need. But this ideal case assumption is far from reality because the capital investment cost is too high for doing that. Therefore, we have suggested a limited DERs number to be implemented in the distribution system, and due to that number, we have minimized the power loss objective function [42]. This constraint can be formulated as follow:

$$N_{DER} \leq n_{DER} \quad (20)$$

We have considered n_{DER} and N_{DER} as the maximum DERs specified number and DERs determined number, respectively.

- DERs size

Same as Eq. (10) that we consider the DERs size limitation for the first scenario, we can use the same formulation for this scenario too [43].

- DERs limitations

The DERs limitation for electricity-generating depends on the DERs type. We have assumed the photovoltaic unit can regularly generate daily electricity from 6:00 am to 6:00 pm. Also, we have adopted wind turbines that continuously generate electricity all the time [44]. Also, we suggest to improve this study the other types of limitation such as environment constraint based on the DER type can be considered as the constraints of the optimization problem.

2.3 The third scenario formulation

The third scenario is multiobjective DERs placement and sizing with considering the distribution system hosting capacity and the former installed DERs in the network. The hosting capacity of the system should calculate before DER placement. The hosting capacity calculation helps to find the permissible size of DER for the placement problem. This scenario is suitable for the electric utilities with several objective functions and has several existing installed DERs in the distribution system. This scenario considers fuel cell units as DERs and the DERs ownership type, and the objective functions are the same as the first scenario.

2.3.1 Objective functions

Decision-makers determine the objective functions as Single-objective or multiobjective functions based on power system requirements based on their system requirements for modifying. The optimization algorithms are the tools for resolution of problems that involves limited resources, and can calculate these objective functions [45]. This section defines the three main objectives important for decision-makers of the DERs placement in the distribution system: cost, voltage deviation, and electricity generation loss.

- Cost objective-function

The cost objective-function is the same as the second scenario, but because of changing the DERs type the Eq. (14) will be changed as follows [9,46]:

$$f_1(X) = \sum_{j=1}^{N_{fc}} C_{fc}(P_{fc}) + cost_{sub} \tag{21}$$

- Voltage deviation objective function

This scenario defines the bus voltage deviation the same as the first scenario (i.e., Eq. (7)) [47], but the results have shown in per unit.

- Power losses objective function

This scenario defines the real power loss, which needs minimization same as the first scenario (i.e., Eq. (8)) [48].

2.3.2 Constraints

- Limitation of voltage

This scenario considers keeping the permissible voltage limits for the network. Same as previous methods, we can use Eq. (9) for this constraint [49].

- Number of DERs

According to hosting capacity analysis, the system decision-maker can select the DER number between 1 to the maximum bus number of the distribution system. The hosting capacity as an input of the optimization algorithm checks whether the size and number of applied DER for placement are acceptable for the system or not. The mentioned selection is fulfilled based on decision-maker limitation for DERs installation. This scenario suggests ignoring the case that DERs number equal to the maximum bus-number because, in this situation, the placement problem change to DERs connection that maximizes each bus's hosting capacity. Therefore, we will ignore the benefit from placement and optimizing objective functions in this situation. We consider the formulation of this constraint the same as Eq. (20) shown in the second scenario.

- Size of DER

This scenario considers the DERs size limitation for this scenario with the same formula as Eq. (10) [43].

- Thermal limitation

The thermal limitation can be applicable when the DERs type is fuel cells. When the fuel cell units are implemented in the case of combined heat and power (CHP) for increasing their efficiency, the thermal limit is an important issue. The thermal limitation should be considered in the DERs placement problem by selecting the CHP fuel cell as DERs type. The readers can find the details of this feasible technology in [50].

2.4 The fourth scenario formulation

The last scenario presents the optimal DERs operation schedule in a virtual power plant. Because all distribution system buses may have DERs connection, DERs placement is not the aim. The DERs ownership type can be all types, including Customer-Centric, Utility-Centric, Third-Part-Centric, and a combination of all. This scenario's primary purpose is finding optimal dispatch of DERs, ESSs, and microgrids in a VPP. In this regard, the objective functions are greenhouse gas emissions and the annual power generating cost. This thesis presents a new hybrid optimization algorithm for minimizing the mentioned objective functions.

2.4.1 Objective functions

- annual power generating cost objective-function

The annual power generating cost objective-function as the first objective function of this scenario is defined as follows:

$$
\begin{aligned}
&C_{Annual} = \sum_{i=1}^{a}\left(\frac{CapIDG_i CIDG_i}{A_{IDG}} + M_{IDG}\right) + \sum_{i=1}^{b}\left(\frac{CapIESS_i\, CIESS_i}{A_{IESS}} + M_{IESS}\right) + \\
&\sum_{k=1}^{n}\sum_{i=1}^{c}\left(\frac{CapDG_{i,k} CDG_{i,k}}{A_{DG}} + M_{DG}\right) + \sum_{k=1}^{n}\sum_{i=1}^{d}\left(\frac{CapESS_{i,k} CESS_{i,k}}{A_{ESS}} + M_{ESS}\right) + \\
&\sum_{k=1}^{n}\sum_{i=1}^{c}\sum_{j=1}^{t} OutDG_{i,j,k} McDG_{i,j,k} W_j + \sum_{i=1}^{a}\sum_{j=1}^{t} OutIDG_{i,j} McIDG_{i,j} W_j + \\
&\sum_{k=1}^{n}\sum_{i=1}^{d}\sum_{j=1}^{t}(OutESS_{i,j,k} - VESS_{i,j,k}) McESS_{i,j,k} W_j + \\
&\sum_{i=1}^{b}\sum_{j=1}^{t}(OutIESS_{i,j} - VIESS_{i,j}) McIESS_{i,j} W_j + \sum_{k=1}^{n}\sum_{j=1}^{t} I_{j,k}\, P_{j,k} W_{j,k} + \\
&\sum_{k=1}^{n}\sum_{j=1}^{t} E_{j,k}\, r_{j,k} + \sum_{k=1}^{n} Pmicrogrid_k(\gamma) + \sum_{i=1}^{a}\sum_{j=1}^{t} IIDG_{i,j}\, PIDG_{i,j} W_{i,j} +
\end{aligned}
\tag{22}
$$

$$\sum_{i=1}^{a}\sum_{j=1}^{t} EIDG_{i,j}\, rIDG_{i,j} + \sum_{i=1}^{a} PIDG_i(\gamma) + \sum_{i=1}^{b}\sum_{j=1}^{t} IIESS_{i,j}\, PIESS_{i,j} W_{i,j} + \sum_{i=1}^{b}\sum_{j=1}^{t} EIESS_{i,j}\, rIESS_{i,j} + \sum_{i=1}^{b} PIESS_i(\gamma)$$

C_{Annual} is the objective function that should be minimized.

- Emission objective function

The second objective function is the emission objective function, that its formulation is the same as the fourth objective function of the second scenario (i.e., Eq. (17)-(19)).

2.4.2 Constraints

- Voltage restriction

We should keep the permissible voltage restriction the same as previous scenarios by Eq. (9).

- The unit restriction for generating power

We should keep the DER power generation less than its capacity. This restriction is formulated as a constraint for the scenario as follow:

$$OutIDG_{i,j} - CapIDG_i \leq 0 \tag{23}$$

for $i = [1, a]$, and $j = [1, t]$

$$(OutIESS_{i,j} - VIESS_{i,j}) - CapIESS_i \leq 0 \tag{24}$$

for $i = [1, b]$, and $j = [1, t]$

$$OutDG_{i,j,k} - CapDG_{i,k} \leq 0 \tag{25}$$

for $i = [1, c]$, $j = [1, t]$, and $k = [1, n]$

$$(OutESS_{i,j,k} - VESS_{i,j,k}) - CapESS_{i,k} \leq 0 \tag{26}$$

for $i = [1, d]$, $j = [1, t]$, and $k = [1, n]$

- discharge-charge rate limitations

We have defined the discharge or charge rate limitations for storage units and ramp limits for generators as follow:

$$\mathrm{RIDG_{l,i}} \leq \mathrm{OutIDG_{i,j+1}} - \mathrm{OutIDG_{i,j}} \leq \mathrm{RIDG_{u,i}}$$

$$\text{for } \mathrm{i} = [1, \mathrm{c}], \quad \mathrm{j} = [1, \mathrm{t}], \text{and } \mathrm{k} = [1, \mathrm{n}] \tag{27}$$

$$\mathrm{OutESS_{i,j,k}} \leq \mathrm{hESS_{u,i.k}} \tag{28}$$

$$\mathrm{VESS_{i,j,k}} \leq \mathrm{hESS_{l,i,k}} \tag{29}$$

$$\mathrm{RDG_{l,i,k}} \leq \mathrm{OutDG_{i,j+1,k}} - \mathrm{OutDG_{i,j,k}} \leq \mathrm{RDG_{u,i,k}} \tag{30}$$

$$\text{for } \mathrm{i} = [1, \mathrm{c}], \quad \mathrm{j} = [1, \mathrm{t}], \text{and } \mathrm{k} = [1, \mathrm{n}]$$

$$\mathrm{OutIESS_{i,j}} \leq \mathrm{hIESS_{u,i}} \tag{31}$$

$$\mathrm{VIESS_{i,j}} \leq \mathrm{hIESS_{l,i}} \tag{32}$$

We suggest to consider the network constraint in cases that the network limitation affects the power flow.

2.5 Chapter considerations

We presented the considered objective functions for all four proposed energy management scenarios. In this regard, we determined the mathematical formulation of the objective functions. Moreover, we evaluated the restrictions of each system. In this regard, we presented the mathematical formulation of the constraints. These formulations are useful in programming the optimization algorithms in all simulating software. The load data will be reported in simulation result chapters.

3 MODELING

Modeling electrical devices and power systems can help to analyze and simulate the whole studying scenarios. In this regard, this chapter explains the proposed modeling used for simulation. The models, including technical and mathematical models, can describe and understand the proposed problems.

3.1 Virtual Power Plant Model

A VPP model used in the thesis contains a combination of microgrids, DERs, ESSs, and loads. These units can participate in the electrical market as independent power plants. The main trading aim of this electrical market is minimizing the cost of generating electrical energy. Moreover, the VPP can participate in the electrical market and buy power for charging the ESSs when the electricity price is minimum. Furthermore, to discharge the ESSs at the electric market's best price, the VPP can decrease obtained power from the controlled load. The VPP structure has the flexibility of implementing all types of DERs, including wind turbines, photovoltaic units, or diesel generators. Besides, coordinating the generators' output power, ESS capacity, and load demands is the VPP core's duty. The VPP core is the energy management system (EMS) [51].

This thesis has used the VPP model in the fourth scenario. We have shown the VPP structure schematic overview using in this thesis in Fig. 1. This figure shows the power and data flow connections between all VPP components. Generally speaking, we have changed the distribution system passive management of centralized systems somehow that energy flows from power plants through the transmission lines to the VPP and then from VPP through the demand's distribution network. The power flow can have a different direction if a substantial power generation occurs in the distribution network. We have explained the microgrid model used in the VPP structure in the next section.

Fig. 1 Model of the proposed virtual power plant.

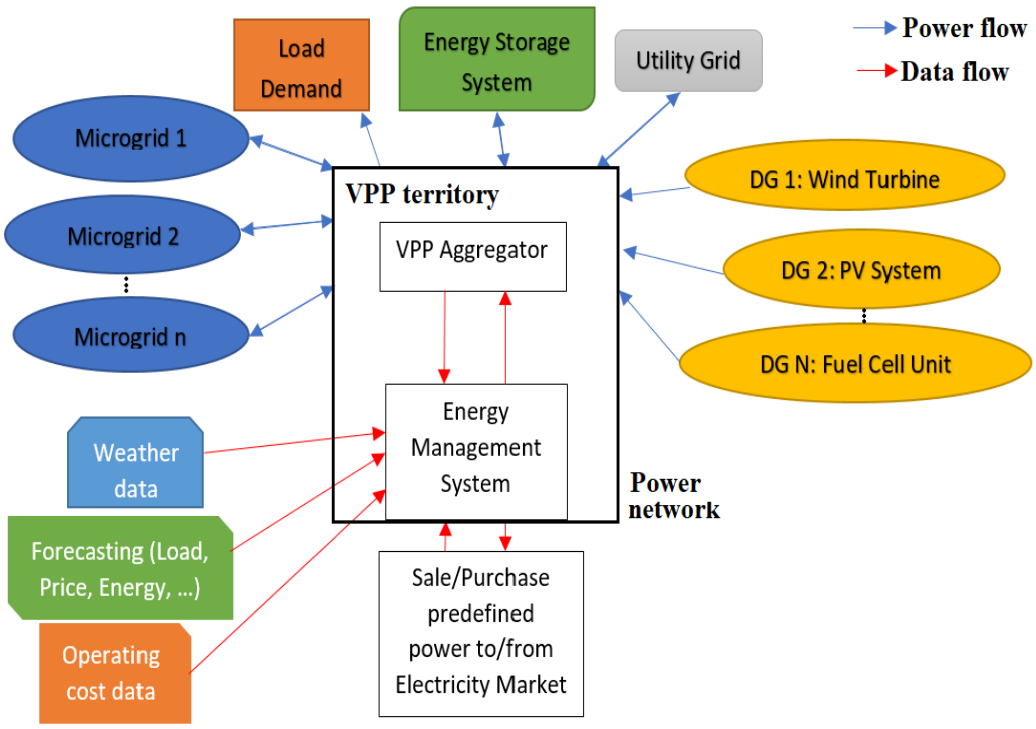


Fig. Ref: [52].

3.2 Microgrid Model

This thesis considers a combination of DERs, EESs, a power distribution infrastructure, the grid connection for import and export, and an EMS as a microgrid. The significant microgrid characteristic is the autonomous capability of operating in an 'islanded' mode when the electricity exchange with the macro-grid is zero. The advantage of implementing microgrids in power systems is increasing the network reliability and efficiency with low greenhouse gas emissions [53].

We have shown the microgrid structure using in the fourth proposed energy management scenario in Fig. 2. This figure shows the microgrid structure schematic overview. The n microgrids of Fig. 1 have different DERs types, as we have demonstrated in Fig. 2. Moreover, Fig. 2 shows the power flow between units. It is noteworthy that various projects may have multiple options in the number and DERs types. Furthermore, the DERs units can connect independently to the VPP or through the microgrid.

Fig. 2 Model of the considered microgrid

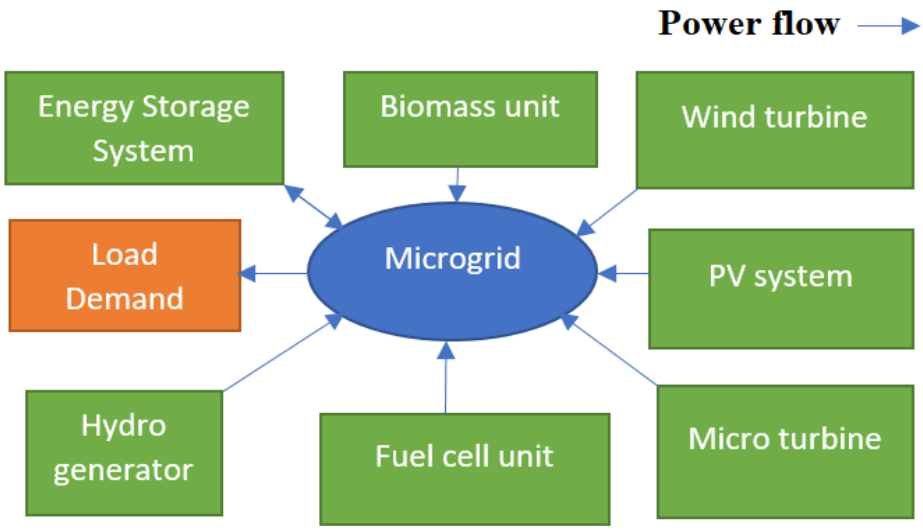


Fig. Ref:[52].

Fig. 3 shows the simulation of a real microgrid as an example. We simulate a hospital and a large hotel in the USA, supplied by a 1MWh generic Lithium-ion battery, the 10 MW photovoltaic units, a utility having a diesel generator (2MW), and the 1.5 MW wind turbines.

Fig. 3 HOMER software simulation of a real microgrid located in the USA

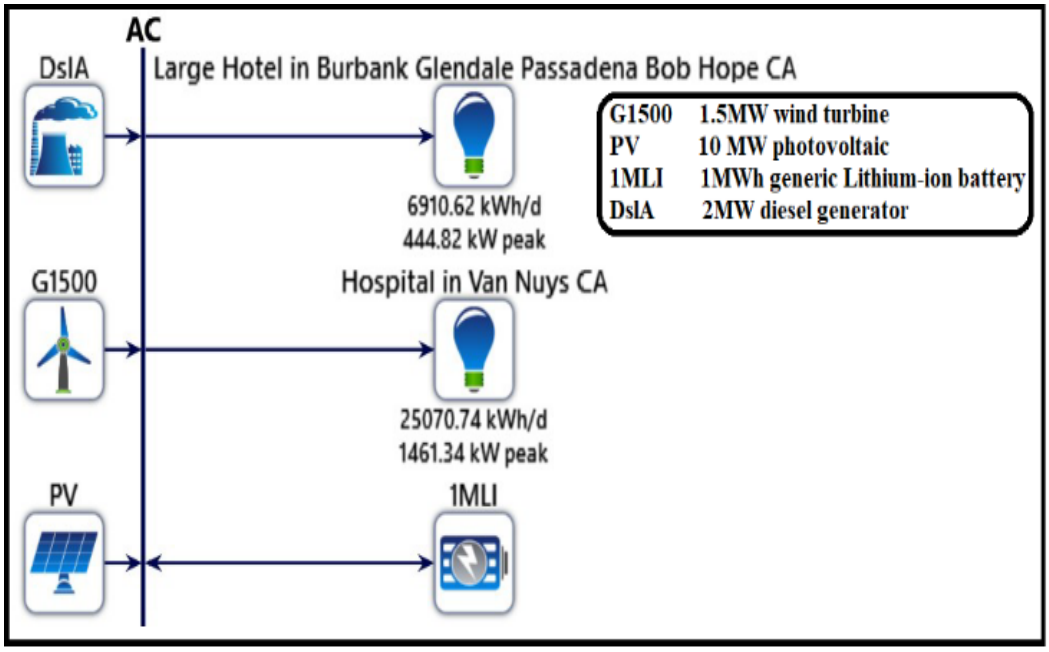


Fig. Ref:[52].

The famous software that has mostly used for the simulation of microgrids including HOMER [54], MATLAB [15], and DER-CAM [55] software. The microgrid analysis, design, and simulation challenge is the variety of uncertainty parameters and design options. Thanks to the mentioned software, this challenge can be smooth. This thesis uses HOMER software for the simulation of microgrids. This software has been industrialized by the US national renewable energy laboratory (NREL).

3.3 Uncertainty and Stochastic Model

Scholars have presented the power system uncertainties modeling in different articles using approximate methods, the Monte Carlo (MC) method, and analytical techniques. The disadvantage of MC is its computational hardness that may lead to decreasing the calculation velocity. On the other hand, MC's advantage is its ability to handle uncertain and complex variables [54]. As we know, the Newton-Raphson method cannot find optimum operating points of radial and meshed distribution systems due to the high R/X ratio of feeders. To solve this problem, a backward-forward sweep (BFS) load flow algorithm is presented by scholars.

In this thesis, we use the MC method for modeling the power system, especially microgrid uncertainties. To avoid repetition, we refer the readers to [56,57] for finding the MC method's detail and the flowchart. Besides, we have used the same MC model in this thesis that the paper [58] has presented. The authors of [58] have implemented the MC model to find the uncertainties in measuring a power system. Another research paper [59] has implemented the uncertainty model for intermittent DERs, market prices, and electrical demand implemented in this thesis. The authors of [59] have explained the MC method's using procedure in the grid search optimization algorithm. The grid search optimization algorithm is a part of the fourth scenario hybrid optimization algorithm that uses the MC method.

3.4 DERs model

Different studies have presented two other PQ and PV models for DERs. Simultaneous or independent three-phase control is the reason for this difference in modeling. It is noteworthy that we should keep the bus voltage magnitude in the

standard range in the PV model [60]. In this thesis, we consider the PQ model for DERs with simultaneous three-phase control.

The challenge of connecting DERs to the power system is the possibility of changing power flow direction or voltage profile. The other challenge of connecting DERs to the power system is the effects of the low value of X/R in the distribution network. Fig. 4 shows two buses of the test network as an example. We determine the voltage drop from bus-1 to bus-2 as follow:

$$\Delta V = (V_1\angle\delta_1) - (V_2\angle\delta_2) = (R + jX)I \tag{33}$$

$$I = \frac{(P+jQ)^*}{V_2{}^*} \tag{34}$$

$$P = P_{DG} + P_{Load} \tag{35}$$

$$Q = Q_{DG} + Q_{Load} \tag{36}$$

$$|\Delta V|^2 = \frac{(RP+XQ)^2+(XP-RQ)^2}{V_2{}^2} \cong \frac{(RP+XQ)^2}{V_2{}^2} \tag{37}$$

Fig. 4 DER's PQ model in the two sample buses of the test network

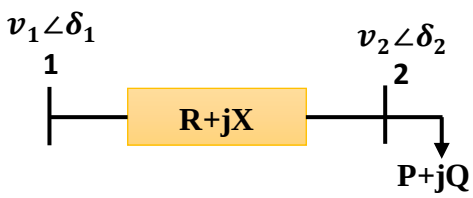


Fig. Ref:[9].

3.4.1 Fuel cell model

This thesis uses the fuel cell model for placement in the distribution system, same as the presented model by Niknam et al. [61]. Section 2 of the mentioned paper has explained the fuel cell model in detail. They have considered the fuel cell units as the PQ model with some limitation in generating electricity.

In this model, the fuel cell combines hydrogen and oxygen to generate electricity, heat, and water. The electrical and thermal powers of fuel cells supply the electrical and thermal distribution system loads. In this model, each cell generates a voltage in

the range of 0.5 to 0.9 V. The generation system contains several cells in series connections.

The authors of [59] have firstly calculated each cell voltage. Then, they have computed each cell's thermodynamic potential that needs measurements of oxygen pressure, hydrogen pressure, and cell temperature. They have also considered voltage drop of electrons and protons passing through the electrolyte and internal electronic resistance. Finally, they have obtained the voltage drop concentration (i.e., reacting gases mass transportation). All needed formulation is available in [59].

3.5 placement and sizing model

The DERs placement and sizing in the distribution system is an optimization problem. Besides, this optimization problem type is a non-convex and mixed integer nonlinear problem. The explained objective functions and constraints can model this optimization problem in section 2. For example, the DERs placement and sizing in the distribution system are described in Ref [62]. The mentioned paper has presented the mathematical model of DER's sitting in its Eq. (10).

3.5.1 Distribution system hosting capacity model

The aim of modeling the hosting capacity is to obtain the maximum total permissible DERs' size in the distribution system. Eq. (38) shows the calculation model for the hosting capacity of the distribution system. We consider a min-max problem in this calculation model. Firstly, we maximize the summation of implemented DERs capacity over primal variables containing bus voltage magnitudes and angles and exchange active and reactive power. After that, we minimize the obtained value over the uncertain parameters with each distribution network bus's real and reactive demands. This model is as follows:

$$HC = \min_{UPr} \max_{PVr} \sum_{n=1}^{N_{bus}} P_n \tag{38}$$

The load variation, including UPr (i.e., first variables) and PVr (i.e., uncertain parameters), affects this hosting capacity model. In this regard, some scholars have presented two approaches, including load ability and voltage variation [32]. The load

ability approach is based on measuring all load variation that the minimum obtained solution of this measuring is the final solution of the hosting capacity. We use the voltage variation approach in this thesis. In this way, we analyze the worst case by robust optimization. We use the voltage variation formulation to obtain the worst-case of the distribution network with DERs. Then, with the worst-case, we can estimate the voltage variation and the maximum hosting capacity. We refer the readers to Ref [32,63,64] for finding an example of the hosting capacity formulation and model with the worst-case-scenario.

The voltage variation approach's main merit is that we do not need to consider all possible daily load variation conditions. It means that we obtain a robust solution against all load variations realizations. Therefore, the load variation cannot affect the hosting capacity calculation.

This thesis suggests keeping some maximum hosting capacity as the power system's future flexibility for development issues. For example, before performing DERs placement and sizing, the electric utility keeps 8 % of the maximum hosting capacity as the reserve capacity. The rest is the value of the hosting degree in the optimization problem.

Increasing the distribution system's hosting capacity can be performed using some techniques such as applying voltage regulators to the power system or reconductoring. Our future research will consider these techniques for the expansion of this research.

We consider the hosting capacity calculation before solving the DER placement and it is the input of optimization algorithm.

3.6 Chapter considerations

We presented all the used models in this thesis in this chapter. In this regard, we determined the mathematical models and concepts that help readers to simulate the proposed scenarios. The presented models contain VPP, microgrid, uncertainty, stochastic, DERs, DERs placement, and distribution system hosting capacity models. The presented models are useful for the other projects that have the same instruments.

4 METHODOLOGY: OPTIMIZATION TECHNIQUES

The proposed energy management scenarios are non-linear, non-convex, and mixed-integer optimization problems. Although the classic mathematical optimization algorithms have perfect accuracy, they are slow in calculation to solve the mentioned optimization problems. The best option for solving non-convex mixed-integer optimization problems is heuristic optimization algorithms. Based on the No Free Lunch Theorem, each optimization problem's best optimization algorithm is different from the other optimization problems. Therefore, this thesis, based on the literature review of suggested algorithm for this specific optimization algorithm, designs the best optimization algorithm for each scenario (i.e., optimization problem). We have proved the superiority of the proposed optimization algorithms by comparing their performances with that scenario's best optimization algorithms. This chapter first explains the applied optimization techniques and then the proposed optimization algorithms of all proposed systems.

4.1 Optimization techniques

4.1.1 The Best Compromise Solution (normalizing) Method

The best compromise solution method is an optimization technique to make all objective functions in the same range. This technique's significant application is in multiobjective optimization problems to apply to the inconsistent objective functions. This thesis defines the ith objective function by a membership function $\mu_i^f(X)$ as follow [65]:

$$\mu_i^f(X) = \begin{cases} \frac{f_i^{max} - f_i(X)}{f_i^{max} - f_i^{min}} & for \quad f_i^{min} \le f_i(X) \le f_i^{max} \\ 0 & for \quad f_i(X) \ge f_i^{max} \\ 1 & for \quad f_i(X) \le f_i^{min} \end{cases} \tag{39}$$

To illustrate the membership function manner, Fig. 5 shows the diverse treatment of the membership function. In this figure, the objective functions' upper, lower limits (i.e., f_i^{max} and f_i^{min}), the continuous manner and a strictly monotonically decreasing treatment are shown. A membership functions $\mu_i^f(X)$ change objective functions (i.e., $f_i(X)$) to have the same range between 0 and 1.

Fig. 5 The membership functions diagram.

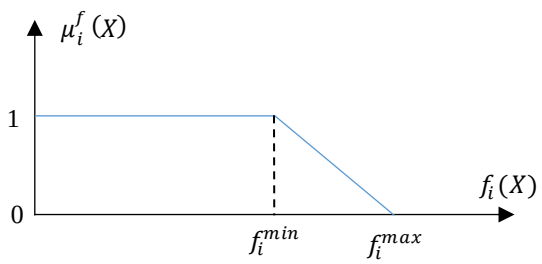


Fig Ref: [66].

The best compromise solution method is a fuzzy method to normalize the objective functions. It means that a membership function (i.e., $\mu_i^f(X)$) shows a fuzzy set (i.e., a value between 0 and 1). As an example, Fig. 6 shows the membership functions for three objective functions, including cost, voltage deviation, and loss.

Fig. 6: Membership functions for cost, voltage deviation, and loss, as three objective functions

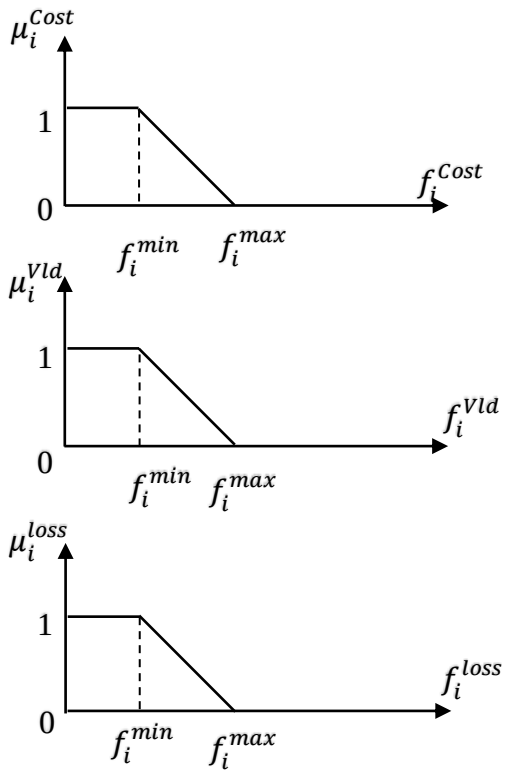


Fig. Ref: [67].

4.1.2 Pareto Method

The optimization technique to show an alternative solution set of multiple conflicting objective functions is the Pareto optimal method. The Pareto technique specifies this alternative solution-set by applying the dominance concept to a multiobjective optimization problem [68]. We have defined the Pareto dominance for two objective functions as follow:

$$\begin{aligned} &\forall i \in \{1,2,3,\cdots,n\}\ (f_1)_i \leq (f_2)_i \\ &\exists j \in \{1,2,3,\cdots,n\}\ (f_1)_j < (f_2)_j \end{aligned} \tag{40}$$

It means that if all components of an objective function vector are less than or equivalent to another objective-function vector value and are strictly less than at least one of the elements, it can dominate another objective-function vector. The non-dominated set of optimal solutions is the Pareto optimal set [69].

4.2 Optimization algorithm for the first scenario

This thesis designs a new modification for the TLBO algorithm to solve the single objective placement and sizing of DERs in the distribution system. This further modification improves the accuracy and convergence velocity of the TLBO algorithm. We have modified the original TLBO by using a new mutation technique [65] to enhance the optimization population item. This improvement in the TLBO algorithm leads to preventing local minimum convergence. All in all, we have connected a new mutation tool to the population part of the TLBO algorithm.

Primarily, we have randomly considered three vectors from the initial population of the TLBO algorithm and called them z_1, z_2, and z_3 in somehow that $z_1 \neq z_2 \neq z_3$. Then, we have calculated a mutation vector $X_k^{mut,i}$ for each feasible solution vector $X_k^i (i = 1,2,\dots,N$ where N is the number of population) by using the following equation:

$$\begin{aligned} &X_k^{mut,i} = X_k^{z_1} + rand(\quad) * \left(X_k^{z_2} - X_k^{z_3}\right) \rightarrow \\ &X_k^{mut,i} = \left[\, X_k^{mut,1}, X_k^{mut,2}, \dots, X_k^{mut,n}\right] \end{aligned} \tag{41}$$

Where n represents the vector components number. Then, we have mixed the target vector with the mutated vector, as follow:

$$X_k^{new} = \begin{cases} X_k^{mut} & if\ rand1(\quad) > rand2(\quad) \\ X_k^i & otherwise \end{cases} \rightarrow$$

$$X_k^{new} = [\, X_k^{new,1}, X_k^{new,2}, \dots, X_k^{new,n}] \tag{42}$$

We should then decide whether the obtained trial vector X_k^{new} can be a member of the optimization population part. It means that this mutation technique effects on the population part of optimization algorithm, and improve this part. For making the decision, we have compared the trial vector X_k^{new} and target vector X_k^i by calculation of their objective functions as follows:

$$X_{k+1}^{new} = \begin{cases} X_k^i & if \quad f(X_k^i) < f(X_k^{new}) \\ X_k^{new} & otherwise \end{cases} \tag{43}$$

Where $f(X_k^i)$ and $f(X_k^{new})$ represent the objective functions of the X_k^i and X_k^{new}, respectively.

This scenario is a single objective, but if we want to use this comparison in multiobjective problems, then we can compare X_k^{new} and X_k^i as follows:

$$X_{k+1}^{new} = \begin{cases} X_k^i & if \quad f(X_k^i)\ dominate\ f(X_k^{new}) \\ X_k^{new} & if \quad f(X_k^{new})\ dominate\ f(X_k^i) \end{cases} \tag{44}$$

If in the above equation none $f(X_k^i)$ and $f(X_k^{new})$ could dominate each other, then, we can utilize the max-min method by using achieved $\mu_i^f(X)$ of Eq. (39) as follows:

$$\alpha_1 = \min\ (\mu_i^1, \mu_i^2, \dots, \mu_i^L),\ \alpha_2 = \min\ (\mu_{new}^1, \mu_{new}^2, \dots, \mu_{new}^L),\ X_{k+1}^{new} = \begin{cases} X_k^i & if \quad \alpha_1 > \alpha_2 \\ X_k^{new} & otherwise \end{cases} \tag{45}$$

Where L represents the objective function's number in the multiobjective problems.

4.2.1 The application (step by step algorithm and flowchart)

In general overview, this algorithm is a population-based algorithm that has one main loop. The random population in this loop tested to satisfied objective functions and constraints. We have considered the following steps to simulate the proposed optimization algorithm for the first energy management scenario as follow:

Step1: Firstly, we have defined all the input data of the optimization algorithm, including loads and network data, population size, line impedance, DERs type and characteristic, constraints, f_i^{min}, f_i^{max}, iterations number, and the number of new and old DERs.

Step2: We have produced the initial population of the TLBO algorithm as follows:

$$X_r = [Location_1, Location_2, \dots, Location_n, P_1, P_2, \dots, P_n]$$

$$r = 1,2, \dots, n_p \tag{46}$$

$$Pop = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_{n_p} \end{bmatrix}_{n_p} \rightarrow F = \begin{bmatrix} F_{11} & F_{21} & F_{31} \\ F_{12} & F_{22} & F_{32} \\ \vdots & \vdots & \vdots \\ F_{1n_p} & F_{2n_p} & F_{3n_p} \end{bmatrix}$$

This equation consists of three objective functions value (i.e., F_{1n_p}, F_{2n_p}, F_{3n_p}) for Nth feasible solution that n_p represents the number of feasible solutions. Moreover, in this equation, the DERs numbers, DERs locations (change between one and the maximum network-bus number), and DERs sizes (change between zero and the nominated capacity) are represented by n, $Location_n$, and P_n, respectively. It is noteworthy that we have considered two types of variables in this equation, including the continuous variable for DERs size and the discrete variable for DERs' location. We have used the round function for discrete variables. We have shown the DERs' places and sizes for each bus of the distribution system by X_1, X_2,..., X_{n_p} in DERs placement problem.

Step3: We have calculated the objective function vectors by Eq. (6), Eq. (7), and Eq. (8). After that, we have normalized them by Eq. (39).

Step4: We have computed Pareto optimal solutions using the obtained normalized objective function vectors, and then we have kept them in the external cache.

Step5: Teacher phase:

We have considered the population column-wise mean, which will give the mean for the particular as:

$$M = [m_1, m_2, \dots, m_n] \tag{47}$$

So far, we have selected a presented Pareto optimal solution of the external cache as a teacher in the TLBO algorithm, and we have called it X_{old} in the random process. Then, we should calculate X^{new} as follows:

$$X_r^{diff} = rand(\quad) * (I_r - R_s * N_r) \tag{48}$$
$$X_{r+1}^{New} = X_r^{Old} + X_r^{diff} \tag{49}$$

We have represented the teaching factor by R_s in this equation that can determine the average value variation amount. We have obtained R_s randomly with equal probability (R_s equals 1 or 2). We have used a random function (i.e., $rand(\quad)$) to produce a random number in the range [0,1]. We have considered the teacher and mean of rth iteration by I_r, and N_r, respectively.

Step6: Learner phase:

In this step, we should check whether each element breaks the operating restrictions or not. In this regard, we make an independent variable equal to the maximum level if it is greater than the top level. On the other hand, we have created an independent variable similar to the minimum level if it is less than the minimum level.

We have calculated the X^{new} vector and we have compared its objective functions with the other external cache vectors found objective functions. We have selected X^{new} as a population member, if its objective functions vector can dominate the other external cache vectors obtained objective functions.

Fig. 7 The Flowchart of the proposed optimization algorithm for the first scenario

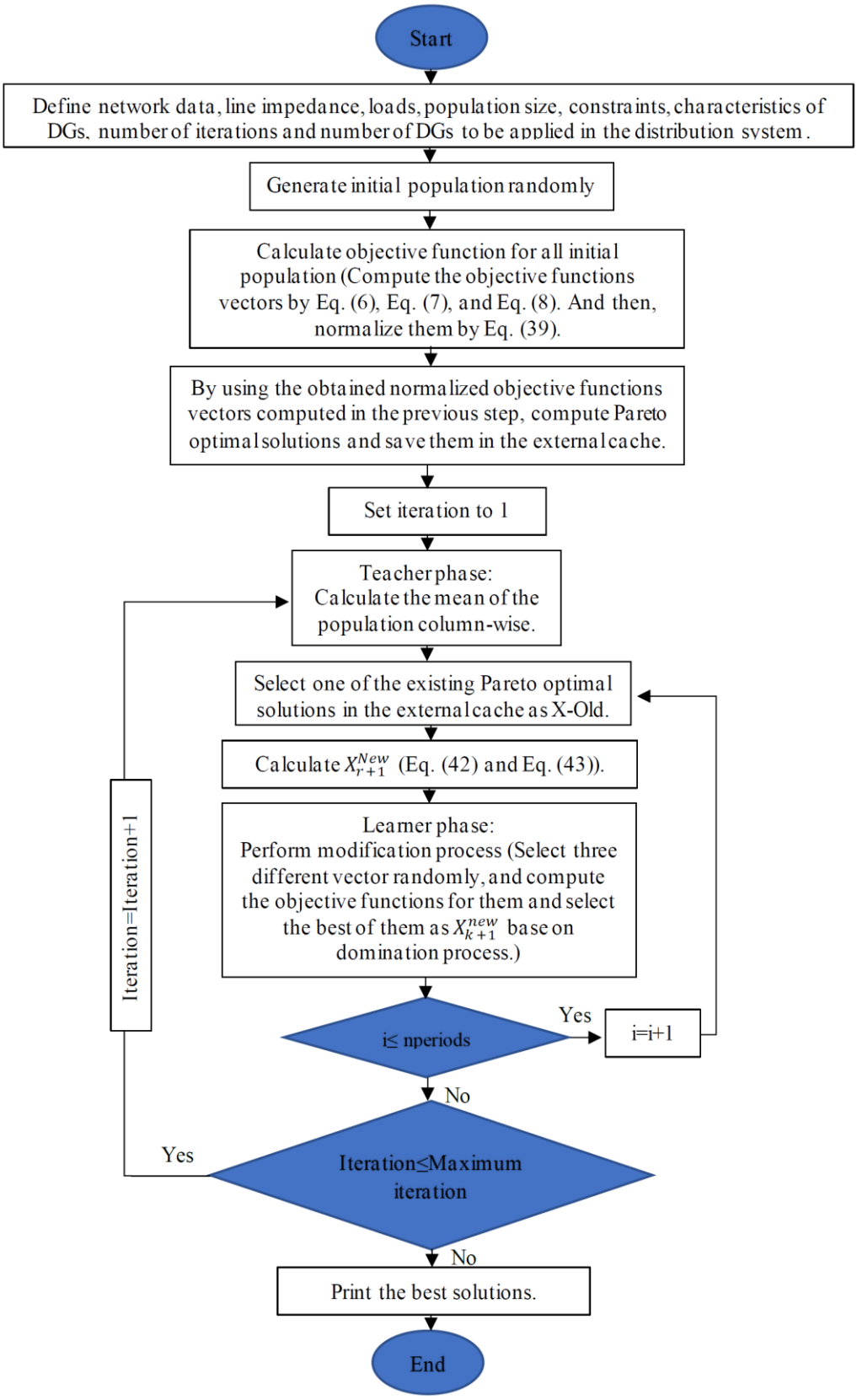


Fig Ref: [66].

Step7: modified algorithm.

In this step, we have determined a new mutation vector by Eq. (41), and next, we have calculated X_k^{new} Eq. (42) and afterward, we have compared its objective functions vector with the other external cache vectors obtained objective-functions by Eq. (43). Lastly, we have added the obtained Pareto optimal solutions to the external cache. It is noted that the infeasible solutions are removed during dominating process that save only non-dominated solutions.

Step8: In this step, we have identified the best solution. Then, we have assigned the best solution as the new teacher. Next, we have modified the students' grades (i.e., X_i) based on the new teacher's knowledge. Finally, we have obtained Pareto optimal solutions.

Step9: In this step, we should assess the non-dominate solutions among the external cache members because, in steps 7 and 8, we have added some non-dominated solutions to the external cache. Therefore, we need to apply the Pareto method to specify non-dominated solutions among all old and new external cache members.

Step10: We should repeat these steps by going back to step5 until the current iteration number equals the programmed maximum number.

We have shown the proposed optimization algorithm flowchart in Fig. 7.

4.3 Optimization algorithm for the second scenario

For the second scenario, we have designed another modification for the TLBO algorithm because considering the multiobjective concept needs increasing calculation accuracy in the optimization algorithm based on reported papers [24]. In this regard, we have combined SA and TLBO algorithm, and also, we have connected the quasi-opposition-based learning technique to the hybrid optimization algorithm. Finding the optimal DERs location and size in the distribution system based on proposed objective functions is the main aim of this scenario. Therefore, the requirements, including concepts and modification techniques for implementing the proposed modification, are explained in this chapter.

4.3.1 Modification of the original TLBO

This thesis presents a new modified TLBO algorithm to check the convergence velocity and accuracy of the TLBO algorithm for solving the second energy management scenario. Firstly, we have combined the SA and TLBO algorithm with improving the optimization population part that leads to preventing unwanted convergence to the local minimum [65]. In other words, we have coupled the TLBO and SA population parts for improving the TLBO algorithm. Secondly, we have added the quasi-opposition-based learning technique to the TLBO algorithm for increasing accuracy. We have used other optimization techniques, including the best compromise solution method and a Pareto concept for a multi-objective approach.

Firstly, we have generated the SA algorithm population for each iteration as follows [60]:

$$X_{k+1}^{sa} = 0.8 * X_k^{old} + rand(\quad) * \left(1.2 * X_k^{old} - 0.8 * X_k^{old}\right)$$
$$X_{k+1}^{sa} = \left[\, X_{k+1}^{sa,1}, X_{k+1}^{sa,2}, \dots, X_{k+1}^{sa,N} \right] \tag{50}$$

Where K represents the vector components number, and the coefficients is determined based on sensitive analysis. Then, we have mixed the target vector and the SA vector as follows:

$$X_K^{new} = \begin{cases} X_K^{SA} & if\ rand1() > rand2() \\ X_K^{v} & otherwise \end{cases}$$
$$\rightarrow X_K^{new} = \left[\, X_K^{new,1}, X_K^{new,2}, \dots, X_K^{new,N} \right] \tag{51}$$

To decide about selecting the trial vector (i.e., X_K^{new}) as a new member of the succeeding population or not, we should compare its objective function with the target vector's (i.e., X_K^{v}) objective-functions as follow:

$$X_{K+1}^{new} = \begin{cases} X_K^{v} & if \quad f(X_K^{v}) < f(X_K^{new}) \\ X_K^{new} & otherwise \end{cases} \tag{52}$$

$f(X_K^{v})$ and $f(X_K^{new})$ represent the objective functions of the X_K^{v} and X_K^{new}, respectively.

In multi-objective problems, we should compare the trial vector's objective function with the target vector's objective functions as follow:

$$X_{K+1}^{new} = \begin{cases} X_K^v & if \quad f(X_K^v)\ dominate\ f(X_K^{new}) \\ X_K^{new} & if \quad f(X_K^{new})\ dominate\ f(X_K^v) \end{cases} \tag{53}$$

If none $f(X_K^v)$ and $f(X_K^{new})$ dominate each other, then we utilize the max–min method by applying the achieved $\mu_x^f(X)$ of Eq. (39) as follows:

$$\begin{aligned} &\alpha_1 = \min(\mu_i^1, \mu_i^2, \dots, \mu_i^L) \\ &\alpha_2 = \min\ (\mu_{new}^1, \mu_{new}^2, \dots, \mu_{new}^L) \\ &X_{k+1}^{new} = \begin{cases} X_k^i & if \quad \alpha_1 > \alpha_2 \\ X_k^{new} & otherwise \end{cases} \end{aligned} \tag{54}$$

4.3.2 Quasi-opposition-based learning

For this scenario, we have combined the modified TLBO with quasi-opposition-based learning (QOBL) optimization technique to increase accuracy (i.e., finding more feasible solutions in closing the global optimum solution). The QOBL technique helps the TLBO algorithm in population initialization and generation jumping [70,71].

We have needed to present some definition to describe the QOBL technique as follows:

- Opposite number

We have defined the opposite number as follow:

$$z^* = a + b - z \tag{55}$$

Where $z\epsilon[a, b]$ represents a real number.

- Quasi opposite number

We have defined the Quasi-opposite number as follow:

$$z_{qo} = rand(c, z^*) \tag{56}$$

Where z represents any real number between $[a, b]$ and $c = \frac{a+b}{2}$.

- Opposite point

We have considered $Z = (z_1, z_2, \dots, z_L)$ that is a point in L dimensional space, where $z_1, z_2, \dots, z_L \epsilon Y$ and $z_l \epsilon [a_l, b_l], l\epsilon 1,2, \dots, L$. Then, we have defined the opposite point (i.e., $Z^* = (z_1^*, z_2^*, \dots, z_L^*)$) as follow:

$$z_d^* = a_l + b_l - z_l \tag{57}$$

- Quasi opposite point:

We have defined the quasi-opposite point as follow:

$$z_d^{qo} = rand(C_d, z_d^o) \tag{58}$$

Where z can be any real number between $[a, b]$,$C_d = \frac{a_d + b_d}{2}$ and $z_d \in [a_d, b_d]; D = \{1,2, \dots, d\}$.

So far, the required definitions to describe the QOBL technique is discussed. In the following section, we explain how to use these definitions in the QOBL technique.

4.3.3 Quasi-oppositional based optimization

We have divided the QOBL technique into two parts: quasi-oppositional-based initialization and quasi-oppositional-based generation jumping. We have shown the quasi-oppositional-based initialization Pseudocode in Fig. 8. Besides, we have demonstrated the Pseudocode of the quasi-oppositional-based generation jumping in Fig. 9. In this figure, we have represented the jumping rate by j^{rr}. The authors of [72] have presented the Pseudocode of the original TLBO algorithm.

Fig. 8: Pseudocode of quasi oppositional based initialization

```
Begin
    For d=1:n_p(n_p=population size)
        For l=1: n_d(n_d=controlvariable)
            x_dl^q0 = rand((a_l+b_l)/2, a_l + b_l - x_dl)
        End
    End
End
```

Fig. Ref: [27].

Fig. 9: Pseudocode of quasi-oppositional based generation jumping

```
Begin
    If rand(0,1)< j^rr
        For d=1: n_p
            For l=1: n_d
                x_dl^q0 = rand((a_l+b_l)/2, a_l + b_l − x_dl)
            End
        End
    End
End
```

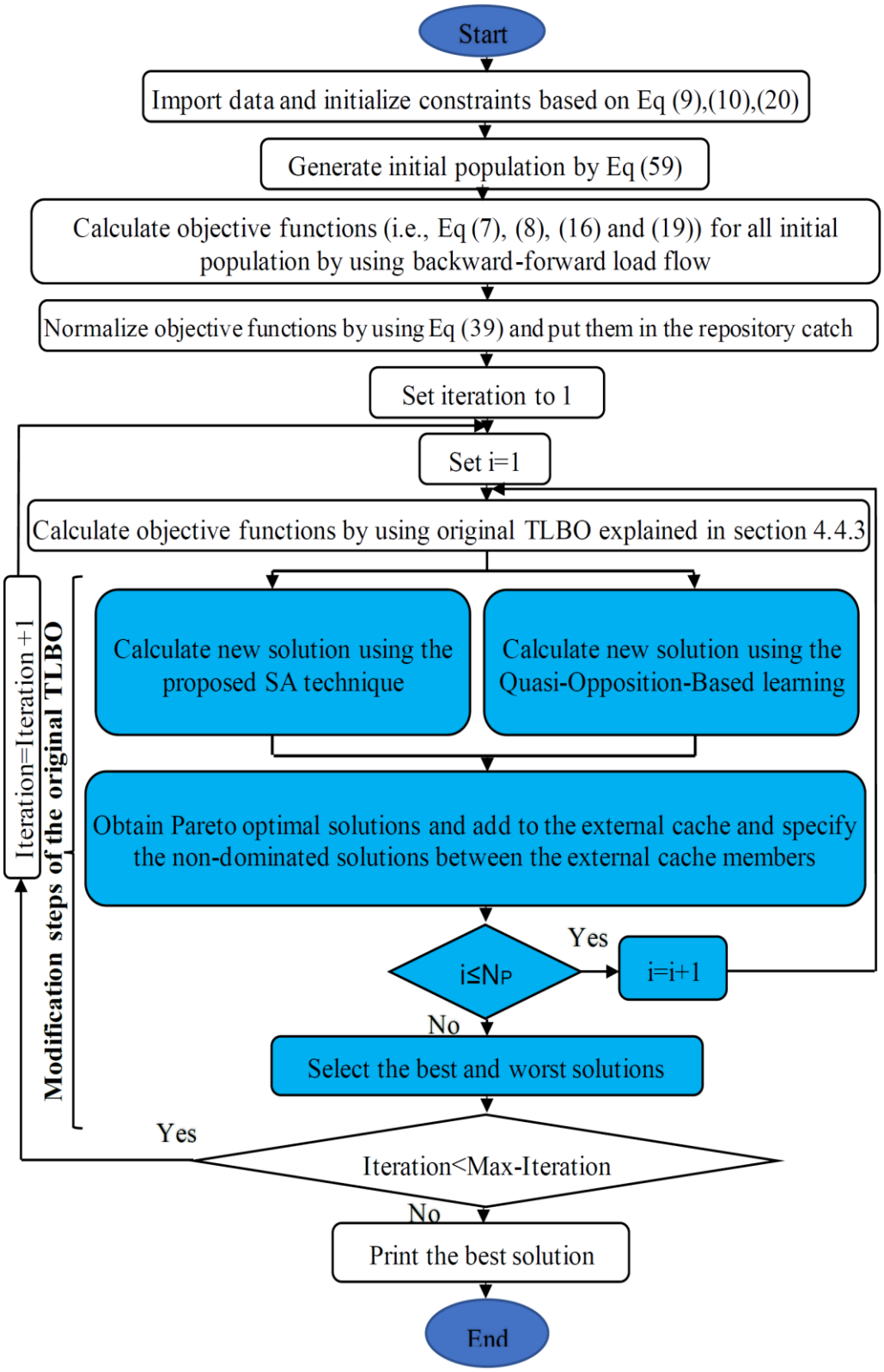
Fig. Ref: [27].

4.3.4 The application (step by step algorithm and flowchart)

For this scenario, we have considered that the electric utility, which is the optimization algorithm's decision-maker, determined the objective functions based on the distribution system improving issues. Then, we have considered the number of permissible DG units by using distribution system hosting capacity calculation. We can find the optimal location and size of DERs in the distribution system with the proposed improved TLBO algorithm with these considerations. We have considered the following steps for implementing the enhanced TLBO algorithm, and also, we have shown its flowchart in Fig.10.

Step1: We have defined the optimization algorithm's inputs such as network and line data, population size, loads data, population size, constraints, DERs characteristics, f_i^{max}, iterations number, and DERs number. These inputs are data and the variable is the real power and location of DERs that in step2 is explained.

Fig.10: Flowchart of the proposed optimization algorithm for the second scenario



Step2: We have produced the initial optimization population as follows:

$$X_r = [Location_1, Location_2, \dots, Location_n, P_1, P_2, \dots, P_n]$$

$$r = 1,2, \dots, n_p$$

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_{n_p} \end{bmatrix}_{n_p} \rightarrow F = \begin{bmatrix} F_{11} & F_{21} & F_{31} & F_{41} \\ F_{12} & F_{22} & F_{32} & F_{42} \\ \vdots & \vdots & \vdots & \vdots \\ F_{1n_p} & F_{2n_p} & F_{3n_p} & F_{4n_p} \end{bmatrix} \tag{59}$$

We have characterized four objective functions for the n_i^{th} feasible solution by F_{1n_p}, F_{2n_p}, F_{3n_p}, and F_{4n_p}. Moreover, we have represented the number of DERs, the DERs location, the DERs size by n, $Location_n$, and P_n, respectively. It is noted that we have considered a discrete variable for DERs location that can change in the range between 1 and the maximum bus number and a continuous variable for DERs size that can change with the range between 0 and the maximum capacity of DERs. Furthermore, we have considered a rounding function for the discrete variables.

Step3: We have calculated the objective function vectors (i.e., Eq. (7), Eq. (8), Eq. (16), and Eq. (19)) by using the backward-forward distribution load flow [73]. In this thesis, we have calculated all objective functions by using the results of backward-forward load flow. Next, we have normalized them by Eq. (39).

Step4: In this step, we have computed Pareto optimal solutions using the obtained normalized objective functions vectors, and then we have saved them in the external cache.

Step5: Teacher phase:

We have computed the population column-wise mean as follow:

$$N = [N_1, N_2, \dots, N_n] \tag{60}$$

In a random process, we have selected an existing Pareto optimal solution in the external cache as a teacher called X_{old}. Eq. (63) and Eq. (64) are the used equations in this calculation.

Step6: Learner phase:

We should check the operating limits of the elements. Firstly, we have reviewed the independent variables; if they are higher than the maximum level, we have made them equal to the top level. If they are less than the minimum level, we have made them similar to the minimum value.

Secondly, we have calculated the objective-functions of X^{new} vector, and then we have compared them with the obtained objective-functions of the existing vectors in the external cache. As a new member, we have selected X^{new} if its related objective-functions vector dominates the related received objective-functions of the existed vectors.

Step7: SA technique modification:

Firstly, using the SA technique, we have calculated X_{K+1}^{new} according to Eq. (52), by using X_K^{new} obtained from Eq. (51). We have compared its objective functions vector with the actual objective functions vector by Eq. (54). Lastly, we have added the Pareto optimal solutions to the external cache.

Step8: QOBL technique modification:

Firstly, we have generated the quasi-oppositional population (QOP) set, and then, we have evaluated the corresponding fitness values.

Step9: We have selected the fittest vectors (i.e., Eq. (50)) required number from X_i , and then we have considered the QOP as a new population set.

Step10: Firstly, we have identified the best solution. Next, we have assigned the obtained solution as the new teacher. After that, we have modified each student score (i.e., X_i) based on the new teacher's knowledge. Finally, we have computed the Pareto optimal solutions, and we have added them to the external cache.

Step11: We should assess the non-dominate solutions among the external cache members because, according to steps 7 and 10, some non-dominated solutions are added to the external cache. We should have non-dominated answers in the external store. Therefore, we must apply the Pareto method to specify the non-dominated solutions among the new and old external cache members.

Step12: We should repeat the algorithm by going to step5 until the current iteration number equals the programmed maximum number.

4.4 Optimization algorithm for the third scenario

We have designed a hybrid optimization algorithm for the third scenario because considering the distribution system hosting capacity and former installed DERs needs a more accurate optimization algorithm. In this regard, we have combined HBMO and TLBO algorithm. Finding the optimal DERs location and size in the distribution system based on proposed objective functions is the main aim of this scenario. Therefore, the requirements, including concepts and modification techniques for implementing the proposed modification, are explained in this chapter.

4.4.1 The proposed TLBO-HBMO algorithm

This section has briefly described the original HBMO and TLBO algorithm because we suppose that the basic knowledge about these optimization algorithms is necessary for interested readers in implementing the proposed optimization algorithm. Finally, we have discussed the hybrid TLBO-HBMO algorithm to approach the proposed scenario in detail.

4.4.2 Honey Bee Mating Optimization (HBMO) algorithm

An insect-based optimization method by considering the mating process of honey bees represents the HBMO algorithm. The HBMO algorithm has been designed based on the behavior of real bees in mating and reproduction. The optimization process results yield from the acceptable number of mating flights. We have represented the mating process of a drone and queen bee by using an annealing function as following [9,74]:

$$Prob(D) = \exp\left[\frac{-\Delta(f)}{S(t)}\right] \tag{61}$$

We have represented the drone D probability for adding his sperm to the queen's spermatheca by $\mathrm{Prob(D)}$. Also, we have characterized the absolute difference between the queen and drone D fitness by $\Delta(\mathrm{f})$. Moreover, we have represented the queen velocity at time t by $S(t)$.

The mating probability has two maximum situations when the drone and queen bee have the same fitness or when the queen bee's speed is high. These situations affect the queen's bee velocity as follow:

$$S(t+1) = \alpha \times S(t) \tag{62}$$

We have represented the falling velocity and energy after each conversion by α (i.e., a number between 0 and 1). We have considered a set of different heuristics for worker bees to improve the brood's genotype rate [75].

All in all, we have summarized the HBMO algorithm in five necessary steps as follows [76]:

1. The first step is the mating process in the HBMO algorithm. In this step, the queen (i.e., definitive answer) randomly selects her pairs from drones. This process continues until fulling the queen's sperm chamber.
2. The combination of queen and drone genes leads to producing a new generation (i.e., temporary solutions).
3. Local search (i.e., breeding and upgrading the bees' baby generation) is the worker's duty (i.e., exploration functions).
4. In this step, we have arranged the workers' fitting-function based on the progress amount that the bees create in the generation-process.
5. We have selected the preferred generation if it is superior to the queen and then, we have replaced it with the queen in the next mating flight.

We have referred the interested readers to [9] for finding the pseudo-codes of the HBMO algorithm and explanations of each step.

4.4.3 Teaching Learning Based Optimization (TLBO) algorithm

Students' learning process in two unique classes with two different teachers for a similar substance subject inspires the TLBO algorithm. In this regard, this thesis has assumed the students have a similar insight level understudy. This optimization process has two phases, including teaching and learning phases. In the teaching phase,

we have considered the best-obtained solution as the teacher and the other solutions as learners that should move toward the teacher. In the learning phase, we have considered students can improve their knowledge through interactive activities. We have considered the following formulation for the TLBO algorithm [11,41,77].

- Teaching phase:

We have considered the teacher knowledge to be the best target for students to bring up their learning level. On the other hand, we have considered the teacher only to improve the class average understanding. This consideration depends on the learners' capability that is a random process (i.e., r_i in Eq (64)) with many interfered factors [27].

We have considered the average-knowledge of learners and the teacher' knowledge as $X_{s,t,k}^{best}$, and T_f, respectively. Then, we should try to improve $X_{s,t,k}^{best}$ to achieve T_f. Therefore, we should update the solution as follows:

$$X_{s,t,k}^{new} = X_{s,t,k} + DS_i \tag{63}$$

$$DS_i = r_i \times (X_{s,t,k}^{best} - T_f) \tag{64}$$

We have considered r_i as a random number between [0, 1].

- Learning phase

In this phase, we have considered two different feasible solutions (i.e., X_i, X_j) as learners. We have determined X_i^{New} as follows:

$$X_i^{New} = X_i + rand \times (|X_i - X_j|) \tag{65}$$

If the objective function of X_i^{New} provides less value than X_i, then we replace X_i^{New} by X_i.

4.4.4 The application (step by step algorithm and flowchart)

This thesis designs a hybrid optimization algorithm for the third energy management scenario. We have updated the optimization-population using HBMO and TLBO algorithms simultaneously at each iteration in this new optimization algorithm. In this regard, if we have found the newly achieved solution of TLBO or

HBMO is better than the previous one, then we have replaced the best solution with the old solution. Otherwise, we have saved the existing solution in the external cache.

We have considered the following steps for implementation of the proposed hybrid optimization algorithm:

Step1: Initially, we have considered the input data of the algorithm, including loads data, line impedance, network data, hosting capacity of the network, population size, constraints characteristics of DER, f_i^{max}, numbers of DER, and iterations.

Step2: We have generated the initial optimization-population as follows:

$$X_r = [Location_1, Location_2, \dots, Location_n, P_1, P_2, \dots, P_n] \tag{66}$$

$$r = 1,2, \dots, n_p \tag{67}$$

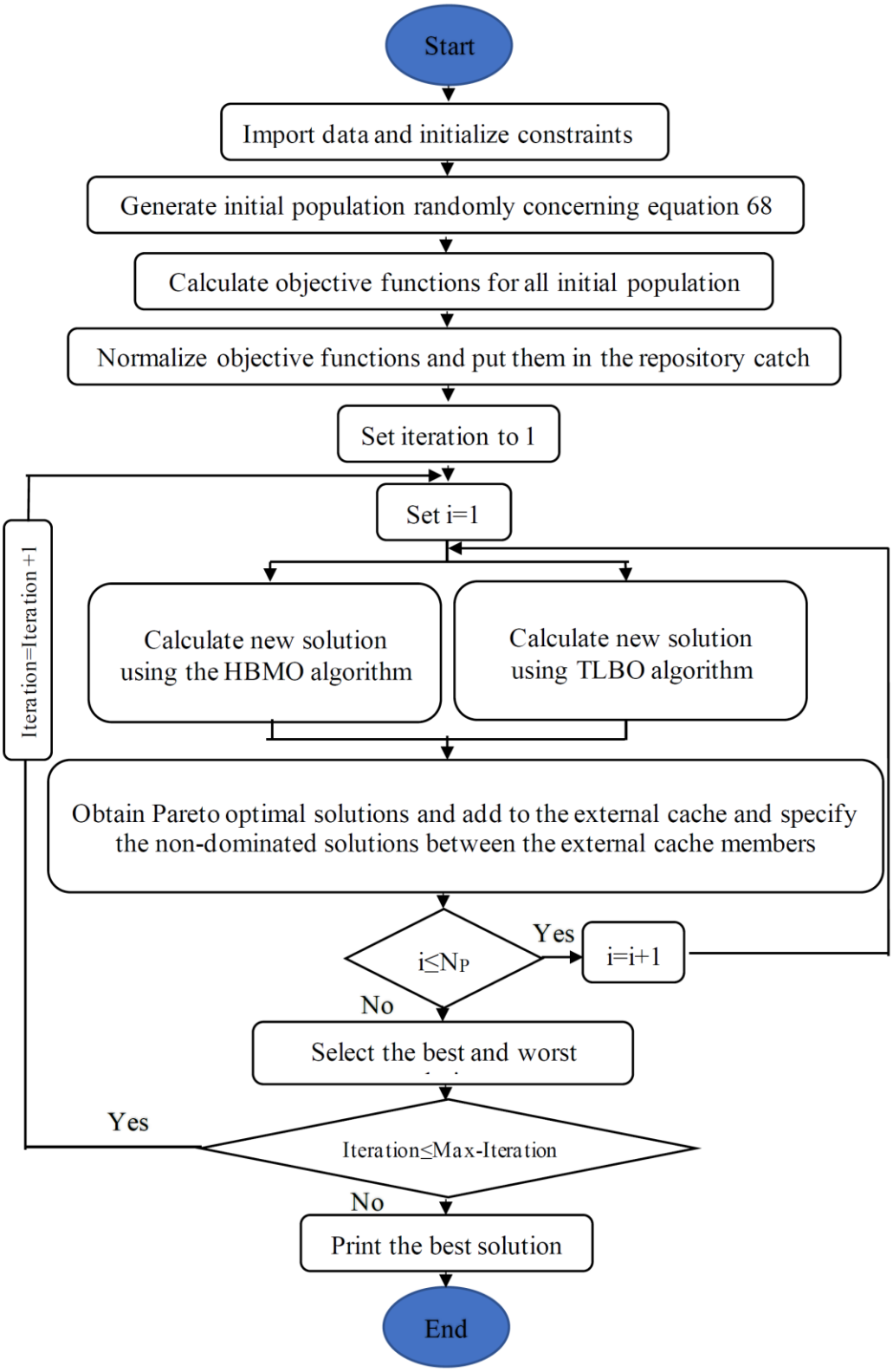
$$Pop = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_{n_p} \end{bmatrix}_{n_p} \rightarrow F = \begin{bmatrix} F_{11} & F_{21} & F_{31} \\ F_{12} & F_{22} & F_{32} \\ \vdots & \vdots & \vdots \\ F_{1n_p} & F_{2n_p} & F_{3n_p} \end{bmatrix} \tag{68}$$

We have characterized the three objective functions for Nth feasible solution as F_{1n_p}, F_{2n_p}, and F_{3n_p}. We have considered the number of feasible solutions as n_p. Additionally, n is the DERs numbers, Location_n represents the DERs location with the range between one and the maximum network-bus number, and P_n is DERs size that changes between zero and the maximum DER nominated capacity. It is noteworthy that we have used two variable types (i.e., discrete and continuous variables). The discrete value denotes the DER location, and the continuous value refers to the DER active power. We used the round function for the discrete variables. We have considered $X_1, X_2, \dots, X_{n_p}$ as DER's locations and sizes at each distribution system bus.

Step3: We have calculated the objective function vectors by using Eq. (7), Eq. (8), and Eq. (21). Next, we have normalized them by Eq. (39).

Step4: We have calculated Pareto optimal solution, and we have saved it in the external cache.

Fig. 11: Flowchart of hybrid TLBO-HBMO algorithm for the third scenario



Step5: We should compute the feasible solutions by using the TLBO and HBMO algorithms.

Step6: In this step, we have computed Pareto optimal solution again, and we have saved it in the external cache.

Step7: We should assess the non-dominate solutions among the external cache members.

According to steps 4 and 6, we have added some non-dominated solutions to the external cache. Therefore, we should use the Pareto technique to assess the non-dominated solutions between the old and new external cache members because the external cache members should be non-dominated solutions.

Step8: We have continued these steps by coming back to step 5 until the current iteration number equals the programmed maximum number.

We have shown the proposed algorithm flowchart in Fig. 11.

4.5 Optimization algorithm for the fourth scenario

This thesis has designed a new hybrid optimization algorithm to solve the fourth energy management scenario. In this regard, we combine two optimization algorithms. Firstly, we have used the grid search algorithm to calculate the feasible solutions. Then, we have used a proprietary derivative-free algorithm to search for the best-optimized solution. We have referred the motivated readers to [78] and [79] for finding these two algorithms' Pseudo-codes.

We have selected the grid search algorithm because of choosing the best parameters for the optimization problem from the set of parameter options reported as its superiority [80]. We have used this ability to compute feasible solutions. Also, we have selected a derivative-free algorithm because of its authority to solve convex optimization problems among optimization algorithms [81]. We have used a derivative-free algorithm to find the best determined feasible solutions. Moreover, we have used the Monte Carlo method to compute the uncertainty and risk impact in the forecasting and prediction model that adds the 25 years cost of using the best solution.

All in all, we have used each optimization algorithm's advantages in our purpose to have the best solutions [81,82].

4.5.1 The application (step by step algorithm and flowchart)

We have considered the following steps for applying the proposed hybrid optimization algorithm:

Step 1: We have defined the input data, including the restriction of VPP components, the standard load profile sample, the generators' number, and the power level.

Step 2: In this step, we have calculated the generators' efficiency at the operating points as follows:

$$Efficiency = \frac{gen}{fuel} \tag{69}$$

We have represented the generators' electricity generation at the operating point in J (joule) by *gen*, and *fuel* is the generator's used fuel at the operating point.

Step 3: We have used the grid search algorithm to produce feasible solutions based on the generators' efficiency and inputs.

Step 4: We have defined all problem variables and constraints in this step by using Eq. (9) and Eq. (23)-(32).

Step 5: We have defined the objective functions in this step based on Eq. (19) and Eq. (22).

Step 6: We have calculated the objective functions by considering the constraints and variables using the derivative-free algorithm for feasible solutions. In this regard, we have used HOMER software, whose applied minimization method is the derivative-free algorithm, too.

Step 7: in this step, we should make the generator's scheduled operating time. We have calculated the objective function minimum for all period times based on generators' load demand and efficiency, computed by the derivative-free optimization algorithm. Then, we have used the MC method to determine the power system uncertainty.

Fig. 12 Flowchart of the proposed optimization algorithm for the fourth scenario

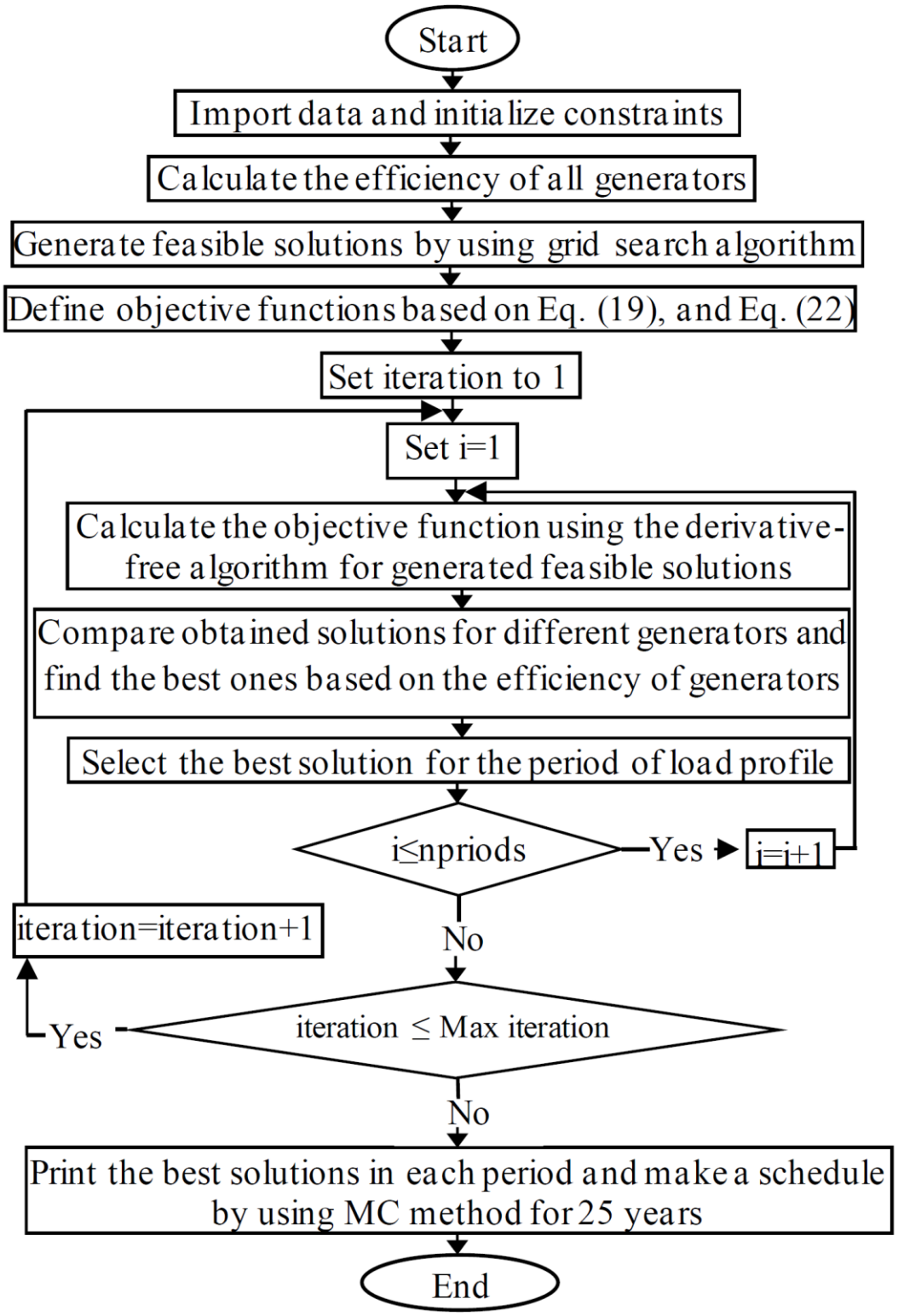


Fig. Ref:[52].

Step 8: Finally, we should check the termination criteria. We have repeated these steps by going to step 2 until the termination criteria (i.e., the last interval of the mission) is satisfied.

We have shown the proposed hybrid optimization algorithm flowchart in Fig. 12. This figure shows all steps of the proposed algorithm as well as the designed loops.

4.6 Chapter considerations

This chapter presented the optimization techniques and algorithms used in this thesis. The first part formulated the general optimization techniques that are used in all proposed energy management scenarios. The second part presented the specifically designed optimization algorithms for each system, intending to increase calculation velocity and accuracy in achieving the optimal solutions for the proposed scenarios. The other optimization projects may benefit from this thesis idea of combining optimization algorithms and presented modifications for the optimization algorithm.

5 SIMULATION RESULTS (SCENARIOS 1 AND 2)

This chapter has presented the simulation results of the first and second energy management scenarios. Both scenario optimization algorithms are two modifications from the same optimization algorithm: the TLBO algorithm. Moreover, we have used the same platform (i.e., an IEEE 70-bus test system) and the same limitations for testing both proposed algorithms. The difference between these two scenarios is in considering objective functions as single or multiobjective functions.

5.1 Simulation Results of the first scenario

We employed the proposed optimization algorithm (i.e., explained in section 4.2) for solving the single objective DERs placement and sizing in an IEEE 70-bus test system. We considered an IEEE 70-bus distribution network with an 11-kV radial network including two substations, four feeders, 70 nodes, and 69 branches. The test system schematic is shown in Fig. 13, while the system data are in Table . We implemented the proposed method in MATLAB software. We performed the simulations in a personal computer having 32 GB RAM, an i7 core processor, and 3.70 GHz. The source of the distribution system data is presented in [74].

Table 3 distribution system data.

Branch number	Sending bus	Receiving bus	R (Ω)	X (Ω)	P (kW)	Q (kVAr)
1	1	2	1.097	1.074	100.0	90.0
2	2	3	1.463	1.432	60.0	40.0
3	3	4	0.731	0.716	150.0	130.0
4	4	5	0.366	0.358	75.0	50.0
5	5	6	1.828	1.790	15.0	9.0
6	6	7	1.097	1.074	18.0	14.0
7	7	8	0.731	0.716	13.0	10.0
8	8	9	0.731	0.716	16.0	11.0
9	4	10	1.080	0.734	20.0	10.0
10	10	11	1.620	1.101	16.0	9.0
11	11	12	1.080	0.734	50.0	40.0
12	12	13	1.350	0.917	105.0	90.0
13	13	14	0.810	0.550	25.0	15.0
14	14	15	1.944	1.321	40.0	25.0
15	7	68	1.080	0.734	100.0	60.0
16	68	69	1.620	1.101	40.0	30.0
17	1	16	1.097	1.074	60.0	30.0
18	16	17	0.366	0.358	40.0	25.0
19	17	18	1.463	1.432	15.0	9.0
20	18	19	0.914	0.895	13.0	7.0
21	19	20	0.804	0.787	30.0	20.0

22	20	21	1.133	1.110	90.0	50.0
23	21	22	0.475	0.465	50.0	30.0
24	17	23	2.214	1.505	60.0	40.0
25	23	24	1.620	1.110	100.0	80.0
26	24	25	1.080	0.734	80.0	65.0
27	25	26	0.540	0.367	100.0	60.0
28	26	27	0.540	0.367	100.0	55.0
29	27	28	1.080	0.734	120.0	70.0
30	28	29	1.080	0.734	105.0	70.0
31	70	30	0.366	0.358	80.0	50.0
32	30	31	0.731	0.716	60.0	40.0
33	31	32	0.731	0.716	13.0	8.0
34	32	33	0.804	0.787	16.0	9.0
35	33	34	1.170	1.145	50.0	30.0
36	34	35	0.768	0.752	40.0	28.0
37	35	36	0.731	0.716	60.0	40.0
38	36	37	1.097	1.074	40.0	30.0
39	37	38	1.463	1.432	30.0	25.0
40	32	39	1.080	0.734	150.0	100.0
41	39	40	0.540	0.367	60.0	35.0
42	40	41	1.080	0.734	120.0	70.0
43	41	42	1.836	1.248	90.0	60.0
44	42	43	1.296	0.881	18.0	10.0
45	40	44	1.188	0.807	16.0	10.0
46	44	45	0.540	0.367	100.0	50.0
47	42	46	1.080	0.734	60.0	40.0
48	35	47	0.540	0.367	90.0	70.0
49	47	48	1.080	0.734	85.0	55.0
50	48	49	1.080	0.734	100.0	70.0
51	49	50	1.080	0.734	140.0	90.0
52	70	51	0.366	0.358	60.0	40.0
53	51	52	1.463	1.432	20.0	11.0
54	52	53	1.463	1.432	40.0	30.0
55	53	54	0.914	0.895	36.0	24.0
56	54	55	1.097	1.074	30.0	20.0
57	55	56	1.097	1.074	43.0	30.0
58	52	57	0.270	0.183	80.0	50.0
59	57	58	0.270	0.183	240.0	120.0
60	58	59	0.810	0.550	125.0	110.0
61	59	60	1.296	0.881	25.0	10.0
62	55	61	1.188	0.807	10.0	5.0
63	61	62	1.188	0.807	150.0	130.0
64	62	63	0.810	0.550	50.0	30.0
65	63	64	1.620	1.0101	30.0	20.0
66	62	65	1.080	0.734	130.0	120.0
67	65	66	0.540	0.367	150.0	130.0
68	66	67	1.080	0.734	25.0	15.0

Table. Ref: [74]

Fig. 13 The Standard IEEE 70 bus system

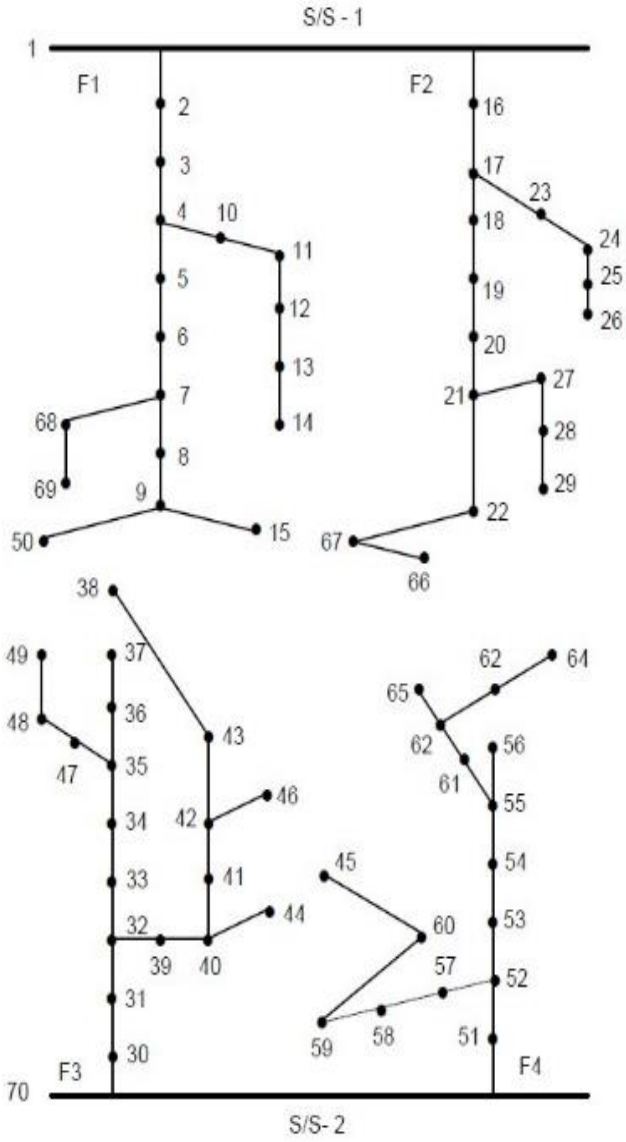


Fig. Ref: [74]

We displayed the calculated three objective functions (i.e., cost, loss, and voltage deviation) in Table 4. We presented their formulations in section 4.2. To compare the proposed algorithm results (i.e., MOTLBO) with other famous optimization algorithms (i.e., GA, HBMO, and TLBO), Table shows three different results objective functions in single-objective mode. The table also offers the best, average, and worst results from all the optimization algorithms mentioned. The proposed optimization algorithm results are smaller than the others in all case studies, which show its superiority in minimizing the objective functions. It is noteworthy that all the

results of this thesis for voltage deviation are shown in the percent of per unit for the mean absolute voltage deviation. For example, 2.55 pu for voltage deviation means 2.55 percent of mean absolute voltage deviation.

Table 4 Accuracy comparison of optimization algorithms for 50 Trails

Objective	Algorithm	Average	Best result	Worst result
f_1 [cost ($)]	GA	6.531×10^7	6.512×10^7	6.568×10^7
	HBMO	6.517×10^7	6.499×10^7	6.540×10^7
	TLBO	6.493×10^7	6.474×10^7	6.511×10^7
	MOTLBO	6.453×10^7	6.433×10^7	6.502×10^7
f_2 [voltage deviation (pu)]	GA	2.55847	2.56384	2.58964
	HBMO	2.55784	2.54194	2.56985
	TLBO	2.52719	2.51515	2.54573
	MOTLBO	2.51102	2.50598	2.53169
f_3 [loss (kWh)]	GA	132.7814	129.5982	135.8975
	HBMO	128.4562	128.0254	129.8372
	TLBO	127.0255	126.2418	128.2651
	MOTLBO	126.0288	125.0252	127.2222

Table. Ref: [38].

Table 5 presents the comparison of the proposed optimization algorithm and GA, PSO, and TLBO algorithm for DERs placement in the test system. Note that the decision-maker considers 12 fuel cell units (100kW) as DERs for the optimization placement problem. This table analysis shows that the best locations for DERs by all mentioned optimization algorithms are practically the same. The difference is the calculation velocity shown by the CPU time in the table. We simulated all the results mentioned in this table in one computer for all optimization algorithms. Moreover, this table results prove the proposed algorithm's superiority in calculation velocity in achieving the optimal point.

We showed the voltage profile changes of the test distribution system with and without the integration of DERs in Fig. 14. We only used one DER for placement in the test distribution system in two different runs for two types of DERs: a micro-turbine (100kW) and a fuel cell unit (200kW). This figure shows the importance of DERs integration that improves the distribution system voltage profile.

Table 5 Calculation velocity comparison and placement comparison of optimization algorithms for three objective functions

Method	Cost ($)	DGs placement (Bus Number)	CPU time (s)
GA [2]	6.508×10^7	1, 2, 3, 13, 21, 29, 31, 33, 34, 44, 52, 53	572.63
PSO [4]	6.480×10^7	1, 2, 3, 14, 21, 29, 31, 33, 34, 44, 52, 53	354.2
HBMO [13]	6.489×10^7	1, 2, 3, 14, 21, 29, 31, 33, 34, 44, 52, 53	102.3
TLBO	6.471×10^7	1, 2, 3, 14, 21, 29, 31, 33, 34, 44, 52, 53	75.26
MOTLBO	6.432×10^7	1, 2, 3, 14, 21, 29, 31, 33, 34, 44, 52, 53	70.32
Method	Voltage deviation (pu)	DGs placement (Bus Number)	CPU time (s)
GA[2]	2.54787	10, 12, 13, 18, 28, 34, 35, 44, 51, 53, 66, 67	445.12
PSO[4]	2.52588	11, 12, 13, 18, 28, 34, 35, 44, 51, 53, 66, 67	226.18
HBMO[13]	2.52325	11, 12, 13, 18, 28, 34, 35, 44, 51, 53, 66, 67	124.1
TLBO	2.51255	11, 12, 13, 18, 28, 34, 35, 44, 51, 53, 66, 67	115.67
MOTLBO	2.50598	11, 12, 13, 18, 28, 34, 35, 44, 51, 53, 66, 67	110.52
Method	Power losses (KWh)	DGs placement (Bus Number)	CPU time (s)
GA[2]	128.3258	6, 7, 8, 23, 30, 31, 41, 44, 58, 59, 66, 67	147.21
PSO[4]	127.1574	7, 8, 9, 23, 30, 31, 41, 44, 58, 59, 66, 69	306.81
HBMO[13]	126.2312	6, 8, 9, 23, 30, 31, 41, 44, 58, 59, 66, 67	123.89
TLBO	126.2258	6, 8, 9, 23, 30, 31, 41, 44, 58, 59, 66, 67	110.56
MOTLBO	125.0184	6, 8, 9, 23, 30, 31, 41, 44, 58, 59, 66, 67	104.74

Table. Ref: [66].

Fig. 14 Voltage profile comparison for using DER in the test network

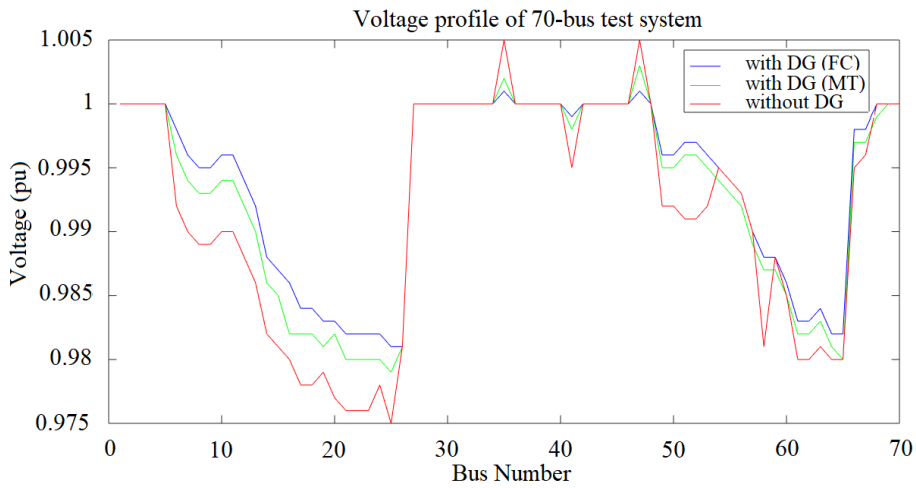


Fig. Ref: [66].

The last comparison of the proposed optimization algorithm with other optimization algorithms (i.e., HBMO and TLBO) is in the convergence plot for different objective functions. The convergence plots in Fig. 15 compare the accuracy and velocity calculation of the mentioned optimization algorithms for three single-objective DERs placement in the distribution system. Accuracy means achieving the minimum feasible solution, while velocity calculation is related to the fewest iteration for achieving this possible solution. The analysis of this figure shows that the proposed optimization algorithm for all the objective functions considered achieved the minimum feasible solution (i.e., the best accuracy among these optimization algorithms) with the fewest iterations (i.e., the best calculation velocity among these optimization algorithms).

Fig. 15 Convergence Comparison of optimization algorithms for three objective functions

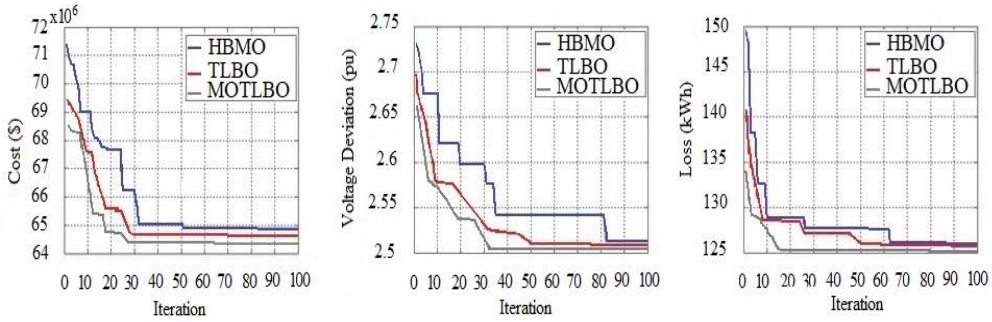


Fig. Ref: [66].

5.1.1 Overview conclusions

The proposed modification in the TLBO algorithm showed the best performance comparing the HBMO and TLBO (i.e., reported as the two best algorithms for this specific optimization problem). Note that the optimal locations achieved with these three best optimization algorithms are the same, but the differences involve minimizing the objective functions and calculation velocity. The results show the best minimized feasible solution obtained by the proposed optimization algorithm in the best time among all the optimization algorithms tested.

5.2 Simulation Results of the second scenario

The second energy management scenario considers the multiobjective concept for DERs placement and sizing in the distribution system. We designed another modification for the TLBO algorithm to optimize objective functions throughout the DERs placement and sizing in the distribution system. The proposed optimization algorithm was implemented in the same test system of the first scenario; its data are gathered/presented in Table and Fig. 13. We analyzed the proposed optimization algorithms in two case studies. The first case study aims to compare single-objective and multiobjective results. In contrast, the second case study aims to analyze the effects of different DERs types in the multiobjective DERs placement problem.

Case study 1: This case study presents single-objective and multiobjective optimization results of the second scenario proposed optimization algorithm. We should obtain the single-objective results for this new algorithm as well as multiobjective results. Comparing the single-objective optimization results of this algorithm and the first scenario algorithm may be interesting for decision-makers. We also presented the multiobjective results that are significant for electric utilities because they can help them decide by finding the effectiveness of objective functions on each other. In this order, we presented the approach of weight options for the objective functions. For this approach, we only showed the nine most acute cases as a sample for decision-makers.

Case study 2: We presented different DERs types in multiobjective DERs placement in the distribution system. Firstly, we assumed all the generators have the same type. Secondly, we considered the varying DERs combinations. The case study results are significant for electric utilities because they can help them find the best DERs for specific projects.

5.2.1 Case study 1: single-objective and multiobjective results

Single-objective results: We presented the single-objective optimization solutions of DERs placement and sizing in the test distribution system for four objective

functions: cost, loss, voltage deviation, and emission. We have to eliminate the Pareto concept of the proposed optimization algorithm (i.e., step 4) because this concept is related to multiobjective problems.

The single-objective products are observed in Table . This table compares the best, average, and worst results from the proposed algorithm, TLBO, HBMO, PSO, and GA algorithms. After 50 trials (i.e., the standard practices for comparing convergence accuracy of optimization algorithms), we achieved the following results.

Table 6: Accuracy comparison of optimization algorithms for 50 trails

Objective	Algorithm	Average	Best result	Worst result
f_1 (\$)	GA	6.531×10^7	6.512×10^7	6.568×10^7
	PSO	6.526×10^7	6.501×10^7	6.555×10^7
	HBMO	6.517×10^7	6.499×10^7	6.540×10^7
	TLBO	6.493×10^7	6.474×10^7	6.511×10^7
	MQOTLBO	6.453×10^7	6.433×10^7	6.502×10^7
$f_2\,(pu)$	GA	2.55847	2.56384	2.58964
	PSO	2.56217	2.55554	2.57894
	HBMO	2.55784	2.54194	2.56985
	TLBO	2.52719	2.51515	2.54573
	MQOTLBO	2.51102	2.50598	2.53169
$f_3\,(kWh)$	GA	132.7814	129.5982	135.8975
	PSO	130.1585	128.9817	132.2548
	HBMO	128.4562	128.0254	129.8372
	TLBO	127.0255	126.2418	128.2651
	MQOTLBO	126.0288	125.0252	127.2222
$f_4\,(kg/h)$	GA	1.22908×10^6	1.21003×10^6	1.25609×10^6
	PSO	1.08601×10^6	1.08002×10^6	1.08928×10^6
	HBMO	1.08250×10^6	1.07382×10^6	1.08530×10^6
	TLBO	1.07601×10^6	1.07225×10^6	1.07912×10^6
	MQOTLBO	1.07559×10^6	1.07204×10^6	1.07906×10^6

The results with more trials (i.e., 100) can be used to determine the superiority of the algorithm convergence velocity and calculation accuracy. Table shows the proposed optimization algorithm can obtain a better solution considering all the objective functions. We employed twelve fuel cell units in this case study, displaying their economic specification in Table , and their coefficients of emission are as follows:

$\alpha = 4.285\frac{Kg}{hMW^2}$,$\beta = -5.094\frac{Kg}{hMW}$, $\gamma = 4.586\frac{Kg}{h}$, $\xi = 1.0 \times 10^{-6}, \lambda = 8.00MW^{-1}$

Table 7. Economic specification of the implemented DG units.

DG Type	Fuel Cell	photovoltaic	Small wind turbine	Bigger wind turbine
Rated capacity (kW)	100	100	10	100
Capital cost ($/kW)	3674	6675	3866	1500
Fuel cost ($/kWh)	0.029	0	0	0
Operation and Maintenance cost ($/kWh)	0.01	0.005	0.005	0.005
Lifetime (year)	10	20	20	20

Table Ref: [9]

We separately showed DER location, CPU time, and the best solution of the four objective functions in Table , Table , Table , and Table , respectively. These tables Compare the best results of the proposed algorithm and other evolutionary algorithms. These tables show that the proposed optimization algorithm superiority over different algorithms has been certified by the execution time and optimized solution.

The Fuel cell units obtained by single objective MQOTLBO for different objective functions in the 70-bus test system are shown in Fig. 16, which shows the optimal DERs locations for each specific objective function.

Fig. 16 Location of 12 Fuel cell units with different objective functions by the single-objective MQOTLBO algorithm in the 70-bus distribution system

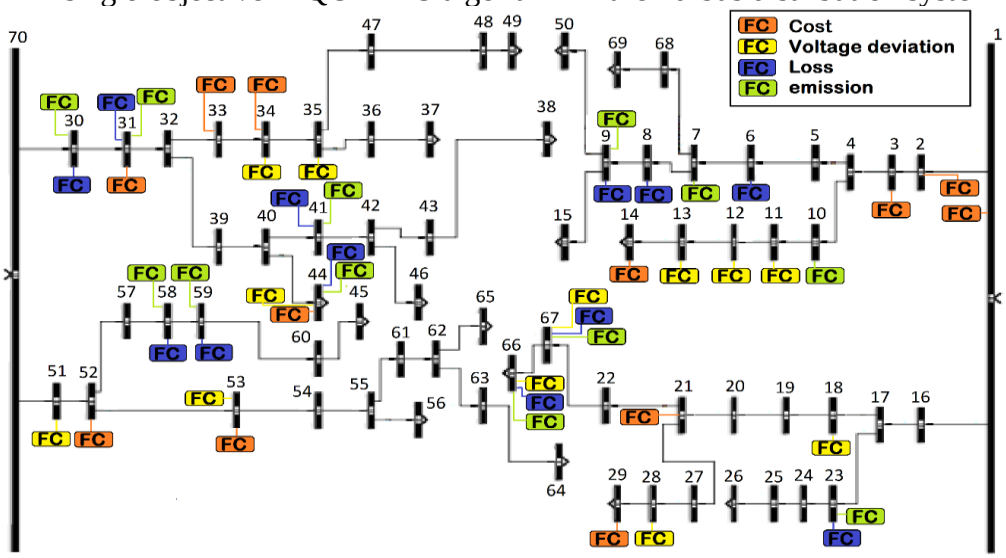


Table 8: Results from the different methods obtained by optimizing the total cost

Method	Cost ($)	DG units placement (Bus Number)	CPU time (s)
GA [36]	6.508×10^{7}	1, 2, 3, 13, 21, 29, 31, 33, 34, 44, 52, 53	572.63
PSO [35]	6.480×10^{7}	1, 2, 3, 14, 21, 29, 31, 33, 34, 44, 52, 53	354.2
HBMO [20]	6.489×10^{7}	1, 2, 3, 14, 21, 29, 31, 33, 34, 44, 52, 53	102.3
TLBO	6.471×10^{7}	1, 2, 3, 14, 21, 29, 31, 33, 34, 44, 52, 53	75.26
MQOTLBO	6.432×10^{7}	1, 2, 3, 14, 21, 29, 31, 33, 34, 44, 52, 53	72.41

Table 9: Results from the different methods obtained by optimizing the voltage deviation of buses

Method	Voltage deviation (pu)	DG units placement (Bus Number)	CPU time (s)
GA [36]	2.54787	10, 12, 13, 18, 28, 34, 35, 44, 51, 53, 66, 67	445.12
PSO [35]	2.52588	11, 12, 13, 18, 28, 34, 35, 44, 51, 53, 66, 67	226.18
HBMO [18]	2.52325	11, 12, 13, 18, 28, 34, 35, 44, 51, 53, 66, 67	124.1
TLBO	2.51255	11, 12, 13, 18, 28, 34, 35, 44, 51, 53, 66, 67	115.67
MQOTLBO	2.50598	11, 12, 13, 18, 28, 34, 35, 44, 51, 53, 66, 67	112.13

Table 10: Results from the different methods obtained by optimizing the total power losses

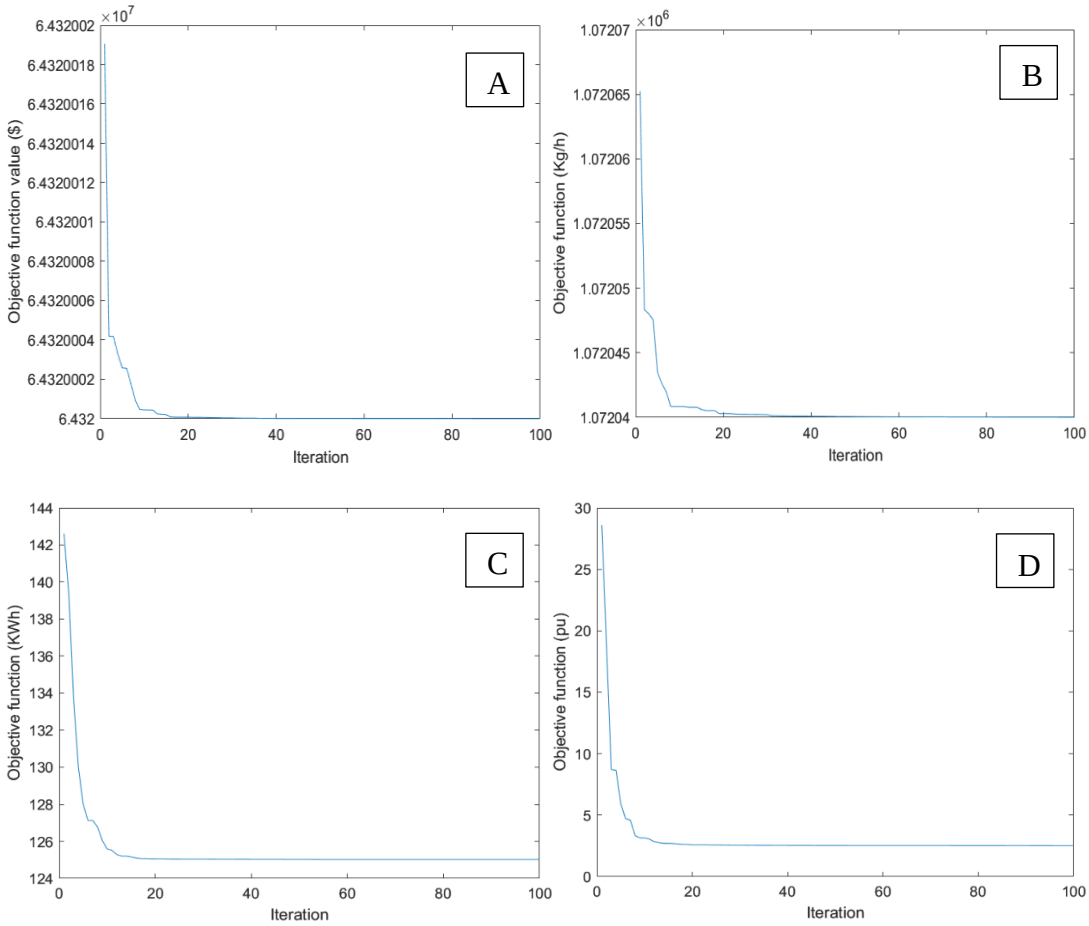
Method	Power losses (KWh)	DG units placement (Bus Number)	CPU time (s)
GA [36]	128.3258	6, 7, 8, 23, 30, 31, 41, 44, 58, 59, 66, 67	147.21
PSO [35]	127.1574	7, 8, 9, 23, 30, 31, 41, 44, 58, 59, 66, 69	306.81
HBMO [18]	126.2312	6, 8, 9, 23, 30, 31, 41, 44, 58, 59, 66, 67	123.89
TLBO	126.2258	6, 8, 9, 23, 30, 31, 41, 44, 58, 59, 66, 67	110.56
MQOTLBO	125.0184	6, 8, 9, 23, 30, 31, 41, 44, 58, 59, 66, 67	106.22

Table 11: Results from the different methods obtained by optimizing the emission

Method	emission (Kg/h)	DG units placement (Bus Number)	CPU time (s)
GA [36]	1.15122×10^6	6, 7, 8, 23, 30, 31, 41, 44, 58, 59, 66, 67	444.46
PSO [35]	1.07550×10^6	7, 9, 10, 23, 30, 31, 41, 44, 58, 59, 66, 67	252.49
HBMO [18]	1.07241×10^6	7, 9, 10, 23, 30, 31, 41, 44, 58, 59, 66, 67	122.78
TLBO	1.07225×10^6	7, 9, 10, 23, 30, 31, 41, 44, 58, 59, 66, 67	115.52
MQOTLBO	1.07204×10^6	7, 9, 10, 23, 30, 31, 41, 44, 58, 59, 66, 67	111.33

Fig. 17 displays the convergence plot of the proposed optimization algorithm. This figure shows the capability of MQOTLBO to converge all the objective functions considered, including total electrical cost, loss, voltage deviation, and emission.

Fig. 17: Convergence curves of MQOTLBO for A: the total electric energy cost, B: total emission, C: total electric losses, and D: voltage deviation



This thesis has used the Friedman test to prove the proposed algorithm superiority among the implemented optimization algorithms. We determined the differences between results groups of optimization algorithms when measuring the dependent variable (i.e., objective function) is ordinal. We refer the readers to [37] to find the formulation and coding of the Friedman test. We obtained Qs (i.e., test statistic) for the objective functions cost, loss, emission, and voltage deviations are 285.996, 276.348, 280.432, and 300, respectively for 100 trials (i.e., n=100), five algorithms (i.e., k=5), and p-value (the level of significance) is considered less than 0.00001. The results are significant at p less than 0.10. See [37] to find the definition, meaning, and formulation of n, p, Q, and k. With the help of Friedman's test, we could see that the best optimization algorithms for this specific optimization problem are MQOTLBO, TLBO, HBMO, PSO, and GA, in this order.

Multiobjective results: We obtained the Pareto optimal solutions, presented in Fig. 18. As observed, the Pareto optimal solutions obtained are well distributed over the trade-off curves. Some objective functions, such as the cost and the power losses, have some conflicting trends.

We compare the obtained Pareto fronts by the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm [83], Multi-objective Genetic Algorithm (MOGA) [84], and the proposed algorithm in Fig. 19. This figure shows the solutions of the proposed algorithm surpass the solutions obtained by MOPSO and MOGA. The proposed algorithm diversity is higher than the other approaches because of the Quasi-opposition mechanisms used throughout the optimization process. We showed only 2 out of 6 positions in Fig. 19 for comparison.

The three objective functions optimized are shown in Fig. 20 using three-dimensional diagrams. Different configurations are presented to help decision-makers (i.e., electric utility) choose the best solution.

Fig. 18: Pareto front obtained using the MQTLBO algorithm

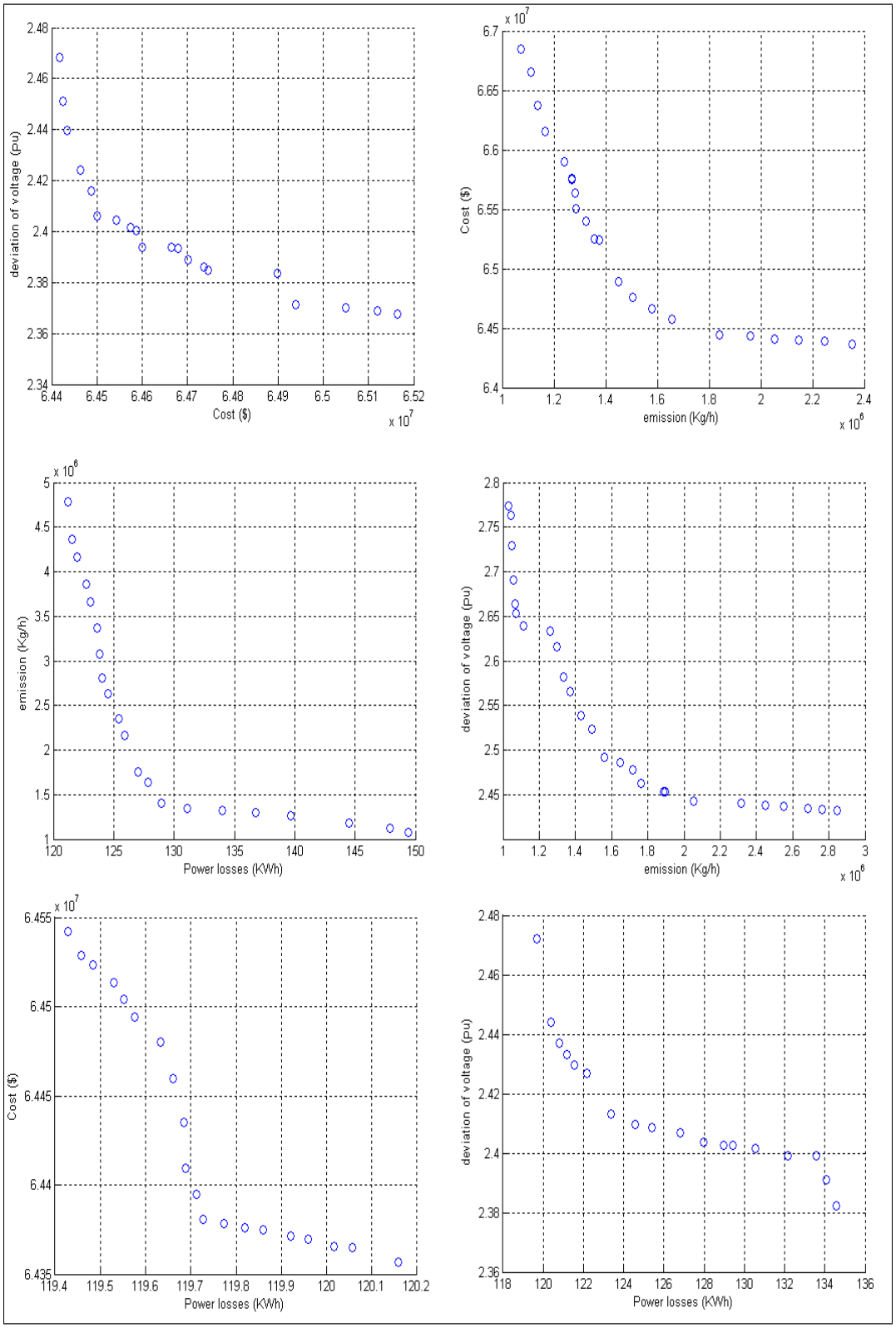


Fig. 19: Comparison of different Pareto fronts obtained by various methods

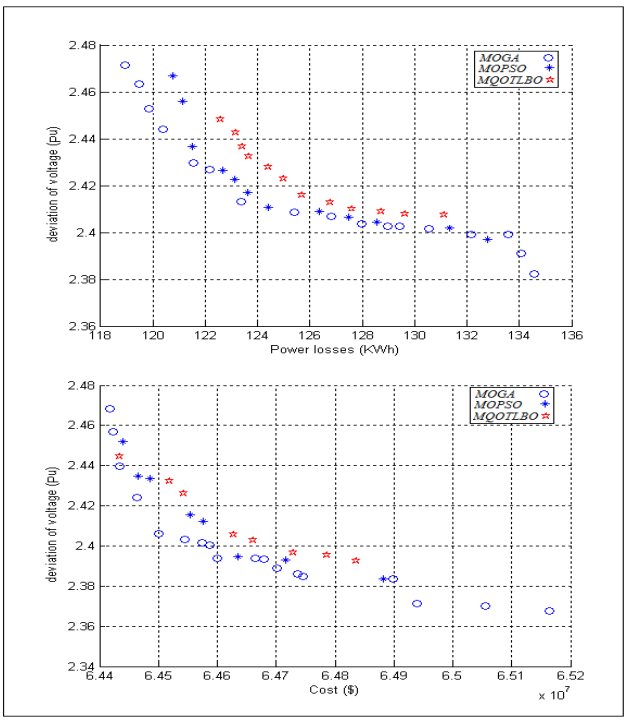
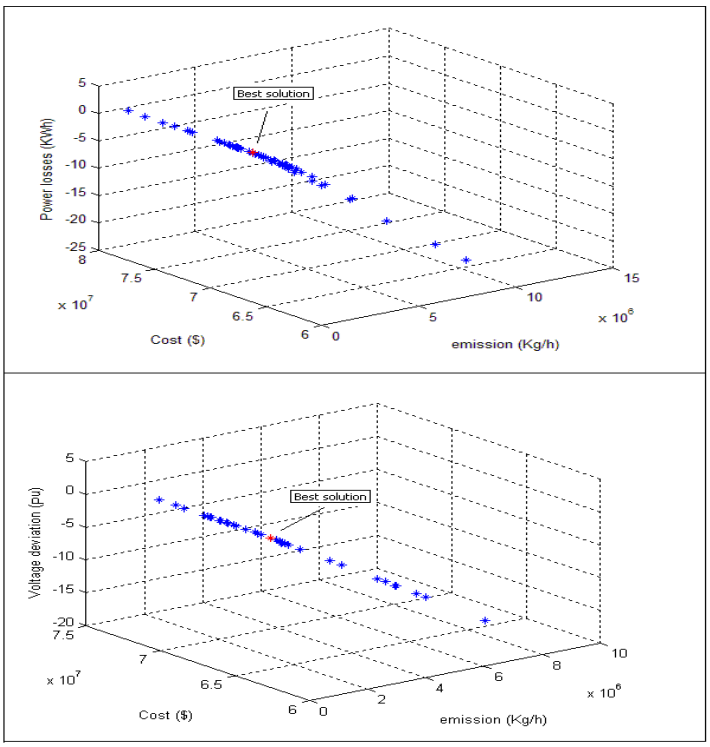


Fig. 20: Pareto front for three objective functions together



We have shown nine cases as a sample of the objective function weight options approach in Table 1. This approach can illustrate the improvement/worsening of each objective function to other ones. We have kept cases I–IV for single-objective optimization results, and the other issues are as follows:

Case V- Considering three objective functions: cost, power losses, and voltage deviation (i.e., f1, f2, and f3).

Case VI- Considering three objective functions: cost, voltage deviation, and emission (i.e., f1, f2, and f4).

Case VII- Considering three objective functions: power losses, voltage deviation, and emission (i.e., f2, f3, and f4).

Case VIII- Considering three objective functions: cost, power losses, and emission (i.e., f1, f3, and f4).

Case IX- Considering all objective functions (i.e., f1, f2, f3, and f4).

We have shown the fourth single-objective optimization in cases I–IV of Table 1. For example, we have considered the cost (i.e., f1) as the single-objective of the case-I, and we have calculated the other objective functions after finding the minimum of f1. We have shown the multiobjective optimization of three objective-functions together in cases V– VIII of Table 1. Lastly, case IX is the multiobjective optimization of the four objective functions together.

We proposed selecting the best compromise solution [9] among all Pareto optimal solutions in Table 1. We have summarized the main points of the obtained results of Table 1 as follows:

– If we compare the obtained results in case-IV and the first part of case-IX, we can find that the first part of case-IX (i.e., 1.4031 per unit) is lower than the voltage deviation of case IV (i.e., 2.5059 per unit). In contrast, three other objective functions (i.e., cost, power loss, and emission) of case IV are lower than the first part of case-IX. With the mentioned observation, we can find that the three objective functions' worsened values in case IV occur due to the reduction of voltage deviation in the first part of case IX.

– We can observe the first and second objective functions in case V have not conflict with each other because when we changed (decreased or increased) w1 and w2, the objective functions did not change.

– We can observe the objectives related to cost or power losses have the same behavior. We can prove this claim by the results of cases I, II, III, IV, and V. We can observe the cases I and III have the same behavior for cost and power losses. It means that when either cost or power loss is minimized, individuality, the other one is also minimized.

Table 12: The proposed algorithm results in the proposed cases with different weights

Cases	Importance				Cost ($)	Power losses (KWh)	Voltage deviation (pu)	Emission (Kgr/h)
	W1	**W2**	**W3**	**W4**				
Case I	-	-	-	-	$6.432*10^7$	125.6982	2.5289	$1.07903*10^6$
Case II	-	-	-	-	$6.501*10^7$	127.4935	2.5801	$1.07204*10^6$
Case III	-	-	-	-	$6.433*10^7$	125.0184	2.5257	$1.07542*10^6$
Case IV	-	-	-	-	$6.457*10^7$	126.8010	2.5059	$1.07447*10^6$
Case V	0.33	0.33	0.33	-	$6.4660*10^7$	128.8938	2.3800	-
	0.2	0.4	0.4	-	$6.4443*10^7$	125.5460	0.1775	-
	0.4	0.2	0.4	-	$6.4443*10^7$	125.5460	0.3732	-
	0.4	0.4	0.2	-	$6.4443*10^7$	125.5460	0.3732	-
Case VI	0.33	-	0.33	0.33	$6.4820*10^7$	-	2.5098	$1.5100*10^6$
	0.2	-	0.4	0.4	$6.4725*10^7$	-	0.3691	$1.0772*10^6$
	0.4	-	0.2	0.4	$6.4725*10^7$	-	0.3691	$1.0752*10^6$
	0.4	-	0.4	0.2	$6.4725*10^7$	-	0.1746	$1.0762*10^6$
Case VII	-	0.33	0.33	0.33	-	135.9335	0.3024	$1.0785*10^6$
	-	0.2	0.4	0.4	-	135.9335	0.3808	$1.0785*10^6$
	-	0.4	0.2	0.4	-	135.9335	0.3708	$1.0785*10^6$
	-	0.4	0.4	0.2	-	133.5985	0.1561	$1.0808*10^6$
Case VIII	0.33	0.33	-	0.33	$7.6062*10^7$	150.4555	-	$1.0757*10^6$
	0.2	0.4	-	0.4	$6.8058*10^7$	148.2527	-	$1.0807*10^6$
	0.4	0.2	-	0.4	$6.8059*10^7$	126.2527	-	$1.0807*10^6$
	0.4	0.4	-	0.2	$6.8057*10^7$	130.0764	-	$1.0807*10^6$
Case IX	0.25	0.25	0.25	0.25	$7.6813*10^7$	141.9335	1.4031	$1.2657*10^6$
	0.1	0.3	0.3	0.3	$7.7172*10^7$	139.2145	1.3051	$1.1659*10^6$
	0.3	0.1	0.3	0.3	$7.6063*10^7$	140.7865	1.2747	$1.2554*10^6$
	0.3	0.3	0.1	0.3	$7.5772*10^7$	138.8321	1.7014	$1.2453*10^6$
	0.3	0.3	0.3	0.1	$7.6270*10^7$	133.3472	0.3909	$1.2873*10^6$

– We can observe that the cost and emission objective functions are conflicting with others. In cases I, II, III, IV, when the cost function is improved, the emission function is worsened and vice versa.

5.2.2 Case study 2: Analysis of DERs Types

Same generators: We have presented the effects of changing the DERs types in the second case study's proposed optimization problem. We have employed 10 kW and 100 kW wind turbines, photovoltaic units, and fuel cell units, that their economic specification is shown in Table . It is noted that the photovoltaic units and wind turbines are considered to generate power.

We have shown DERs placement results when all DERs are similar to each other in Table 1. This table shows that when all 12 DERs are fuel cell units, the cost function is the minimum compared with the different used DERs types. On the other hand, we can observe the other used DERs do not have emissions while fuel cell units have.

Intermittent generating power by some renewable resources such as wind power and solar power is generally criticized. Therefore, they should be combined with other continuous power generators. We used wind turbines or photovoltaic units as all power generators because obtained simulation results can help the decision-makers select a combination of renewable resources.

Table 13: Comparison of using different types of DG units

DG Type	cost($)	Voltage deviation(pu)	Power losses(kWh)	emission (kg/h)
10 kW Wind Turbine	6.884×10^{7}	2.885497	91.1902	0
100 kW Wind Turbine	300.361×10^{7}	2.124123	144.9812	0
Photovoltaic	12.919×10^{7}	2.169854	121.6812	0
Fuel cell with CHP	6.437×10^{7}	2.3854	111.1562	1.07305×10^{6}

The combination of generators: We have applied various small wind turbines, photovoltaic units, and fuel cell units in this case study. We have employed two small wind turbines, two photovoltaic units, and eight fuel cell units in this case study. We have considered the maximum generation of the small wind turbine, photovoltaic unit, and fuel cell unit are 10 kW, 100 kW, and 100 kW.

We have assumed that photovoltaic units can generate power only daily from 6:00 am to 6:00 pm, and small wind turbines can make power all the time. And also, other DERs should compensate for the lack of power generation of photovoltaic units.

We have shown the simulation results of the current case study in Table 1. In this table, we have demonstrated only ten positions of 104 calculated non-dominated solutions. We have shown the optimum values of objective functions, which are optimized separately in boldface. Analysis of the results shows that the cost function's aim is little increased; the emission objective function is decreased; the losses and voltage objective functions have a bit of change.

Table 14: Obtained results for four objective functions and placement

Cost ($)	Voltage deviation(pu)	Power losses(kWh)	emission (ton/h)	Location of fuel cell units	Location of photovoltaic units	Location of Wind units
8.426×10^{7}	**2.569853**	**134.6857**	**1.024×10^{6}**	**4,7,12,14,21,29,31,33**	**22,69**	**56,57**
8.487×10^{7}	2.552981	135.7412	1.072×10^{6}	5,11,22,34,35,44,47,49	15,66	56,60
8.506×10^{7}	2.694219	119.5599	1.065×10^{6}	6,8,18,23,31,33,39,48	66,69	5,26
8.518×10^{7}	**2.727727**	**116.9998**	**1.03×10^{6}**	**9,23,30,31,41,44,58,59**	**22,45**	**57,60**
8.525×10^{7}	2.457199	126.7923	1.069×10^{6}	11,18,40,47,50,59,62,64	45,66	32,35
8.510×10^{7}	2.777587	127.1248	1.066×10^{6}	11,19,40,44,56,57,60,64	15,45	54,60
8.522×10^{7}	**2.565555**	**128.7498**	**1.014×10^{6}**	**11,17,43,44,52,57,62,64**	**15,22**	**5,60**
8.527×10^{7}	2.647498	129.7459	1.061×10^{6}	8,9,11,13,50,59,65,69	22,45	60,64
8.533×10^{7}	**2.384455**	**135.1289**	**1.051×10^{6}**	**4,8,11,22,41,46,58,66**	**45,69**	**32,57**
8.542×10^{7}	2.484489	129.3355	1.075×10^{6}	7,12,25,33,44,52,67,69	22,66	54,56

The optimum values of objective functions optimized separately are shown in boldface.

5.2.3 Overview conclusions

The new modification of the TLBO algorithm presented the best performance in single-objective and multiobjective DERs placement and sizing, comparing the best optimization algorithms. The two proposed case studies analyzed the effects of objective functions and DERs types in this optimization problem. To help the decision-makers, we have presented the Pareto optimal solutions and the concept of weighting the objective functions.

5.3 Chapter considerations

This chapter presented the results of two different new modifications for the TLBO algorithm for single-objective and multiobjective DERs placement and sizing on a 70-bus IEEE test distribution system. We compared both proposed optimization algorithms with the best-reported optimization algorithms for DERs placement. The results proved the superiority of these optimization algorithms. It is noteworthy that if we compare the results of these two algorithms for single-objective DERs placement, we could find that they have the same accuracy (they achieved the same results for minimizing single-objective functions). In contrast, the calculation velocity of the first optimization algorithm is better than the second one, but it cannot be used for multiobjective problems. Therefore, the proposed optimization algorithm for single-objective DERs placement has the best results for the first scenario. The proposed optimization algorithm for multiobjective DERs placement has the best products for the second scenario.

6 SIMULATION RESULTS (SCENARIOS 3 AND 4)

This chapter presentes the third and fourth energy management scenarios' simulation results because both scenario optimization algorithms are hybrid optimization algorithms. The third scenario platform is the same as previous scenarios (i.e., an IEEE 70-bus distribution test system), but the limitation is different from prior designs. We have considered hosting capacity calculation and the former installed DERs in DERs placement and sizing in the distribution system in this scenario. The platform of the fourth scenario is a VPP that is different from previous methods.

6.1 Simulation Results of the third scenario

The proposed hybrid optimization algorithm has been implemented in the same test system of the first scenario that its data are gathered in Table and Fig. 13. We have considered the existence of DERs in the distribution system. Table1 shows the locations and characteristics of these DERs [65].

Table15: Existing DERs characteristics

No. of DER	Capacity (kW)	Location	DER price ($)
1	65	5	0.042
2	50	7	0.043
3	60	11	0.044
4	75	25	0.042
5	55	29	0.042
6	80	41	0.043
7	80	47	0.045
8	40	50	0.045
9	95	58	0.044
10	70	66	0.042

Table. Ref: [65].

We have considered the CHP fuel cell units (i.e., the capacity equals 300kW) as new DERs for placement and sizing in the distribution network. Suppose we want to use the proposed optimization algorithm with other DERs types. In that case, we should consider the new type DER limitations in generation power as the constraints

of the proposed optimization algorithm (i.e., the first step of the proposed optimization algorithm). In this thesis, we have used the backward-forward sweep load flow to determine bus data. We refer the readers to [38] for finding this load flow description and details for simulation and implementation.

This thesis determines the distribution system hosting capacity by considering uncertain loads. In this regard, we have considered the changing range of [1226.9kVAr 3059kVAr] and [1792KW 4468kW] for total reactive and real load, respectively. With this consideration, we have obtained the 70-bus test system hosting capacity equals 7355kW. In the proposed distribution system, the existing DERs generation capacity equals 670kW. We have considered 10% of hosting capacity as a reserve capacity for future system development. Therefore, the hosting capacity of this system equals 5949.5kW. Based on the obtained hosting capacity, decision-makers have determined 19 same fuel cells (i.e., the capacity equals 300kW) for placement in the distribution network. We have considered this fuel cell lifetime equal to ten years; we have also assumed the fuel cost, capital cost, and operation and maintenance cost for this fuel cell identical 0.029$/kWh, 3674$/kW, and 0.01$/kWh, respectively.

6.1.1 Single objective optimization

We have considered three objective functions for the third scenario: cost, loss, and voltage deviation for optimization in single-objective mode. We have compared the proposed hybrid optimization algorithm (i.e., TLBO-HBMO) with GA, PSO, TLBO, and HBMO algorithms. The decision-makers who have one feature for improving the distribution system may find these single objective optimization results useful. Therefore, we have presented the single objective optimization results in this chapter.

We have shown the single objective optimization results for each objective function in Table1, Table 1, and Table 1 separately. These tables compare the results of the proposed optimization algorithm with other optimization algorithms. These results for each optimization algorithm contain the best, worst and average results of optimizing the objective functions. Moreover, the CPU time in these tables shows the calculation velocity of each optimization algorithm. Therefore, these tables compare the accuracy (the best obtained feasible solution) and the calculation velocity (i.e.,

CPU time) of the mentioned optimization algorithms. For example, Table 1 shows the minimum loss of 133.8983kW is achieved for the proposed algorithm, which this optimal solution is lower than the other optimization algorithms. Moreover, Table 1 shows this minimum solution has the least CPU time in comparing different optimization algorithms.

Table16: Comparison of average and standard deviation for cost in 40 trials

Algorithm	Average	Standard deviation	Best result	Worst result	DER's placement (Bus number)	CPU time (s)
Genetic	177.2413	1.5019	176.7823	180.4325	4,5,6,13,21,29,31,33,34,44, 49,52,53,55,59,63,65,68,69	85
PSO	175.9156	0.9971	175.1092	179.9832	4,5,6,13,21,29,31,33,34,44, 49,52,53,55,59,63,65,68,69	49
HBMO	175.8611	0.9821	174.0341	179.1902	4,5,6,13,21,29,31,33,34,44, 49,52,53,55,59,63,65,68,69	45
TLBO	170.0013	0.9201	169.1141	171.9430	4,5,6,13,21,29,31,33,34,44, 49,52,53,55,59,63,65,68,69	35
TLBO-HBMO	168.9418	0.6686	168.6734	170.0102	4,5,6,13,21,29,31,33,34,44, 49,52,53,55,59,63,65,68,69	15

Table 17: Comparison of average and standard deviation for loss in 40 trials

Algorithm	Average	standard deviation	Best result	Worst result	DER's placement (Bus number)	CPU time (s)
Genetic	145.8712	1.5682	141.2121	145.1329	10,12,13,18,28,29,31,34,35,44, 49,51,53,55,59,63,65,68,69	78
PSO	142.9871	1.2779	140.8971	144.6545	11,12,13,18,28,29,31,34,35,44, 49,51,53,55,59,63,65,68,69	57
HBMO	142.3315	1.1680	140.0011	144.1417	11,12,13,18,28,29,31,34,35,44, 49,51,53,55,59,63,65,68,69	55
TLBO	134.9465	0.9125	134.0102	135.9214	11,12,13,18,28,29,31,34,35,44, 49,51,53,55,59,63,65,68,69	40
TLBO-HBMO	134.2930	0.4666	133.8983	135.0016	11,12,13,18,28,29,31,34,35,44, 49,51,53,55,59,63,65,68,69	24

Table 18: Comparison of average and standard deviation for voltage deviation in 40 trials

Algorithm	Average	standard deviation	Best result	Worst result	DER's placement (Bus number)	CPU time (s)
Genetic	1.1076	0.1133	0.9921	1.4312	6,7,8,13,23,29,30,31,34,41, 44,52,53,58,59,66,67,68,69	76

PSO	1.1067	0.0795	0.9888	1.4211	6,7,8,13,23,29,30,31,34,41, 44,52,53,58,59,66,67,68,69	44
HBMO	1.1055	0.0532	0.9814	1.3917	6,7,8,13,23,29,30,31,34,41, 44,52,53,58,59,66,67,68,69	40
TLBO	0.6220	0.0495	0.6108	0.6394	6,7,8,13,23,29,30,31,34,41, 44,52,53,58,59,66,67,68,69	32
TLBO-HBMO	0.6155	0.0284	0.5920	0.6311	6,7,8,13,23,29,30,31,34,41, 44,52,53,58,59,66,67,68,69	19

We have presented the single-objective functions convergence plots in Fig 21, Fig 22, and Fig 23. These figures show the results of achieving the optimal solution in 100 iterations. Moreover, these figures compare the convergence plots of the proposed optimization algorithm with those it makes from those. Therefore, these figures compare the accuracy and calculation velocity of the proposed algorithm with those it makes from those. For example, Fig 22 shows the proposed optimization algorithm achieved its minimum point (i.e., less than the other optimization algorithms minimum points) after about 26 iterations. The different optimization algorithms completed their minimum points after 35 and 48 iterations.

Fig 21: Convergence plot for cost with the different optimization algorithms

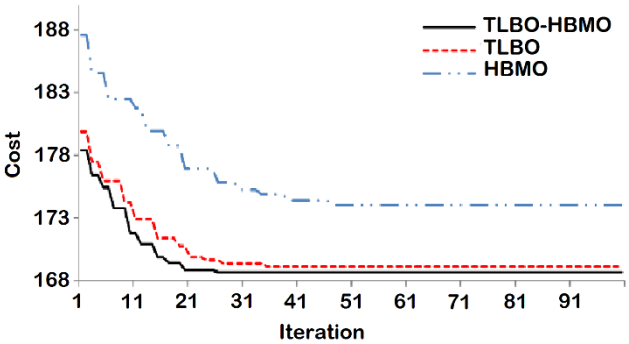


Fig 22: Convergence plot for voltage deviation with the different optimization algorithms.

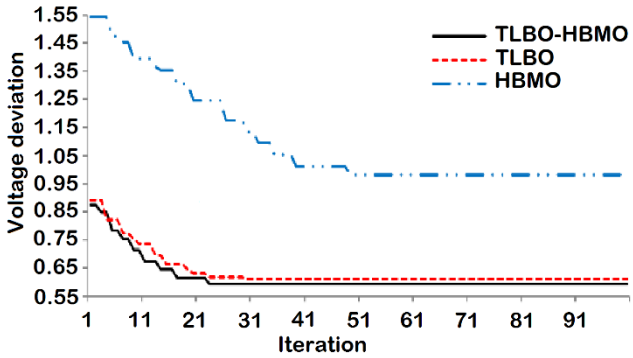
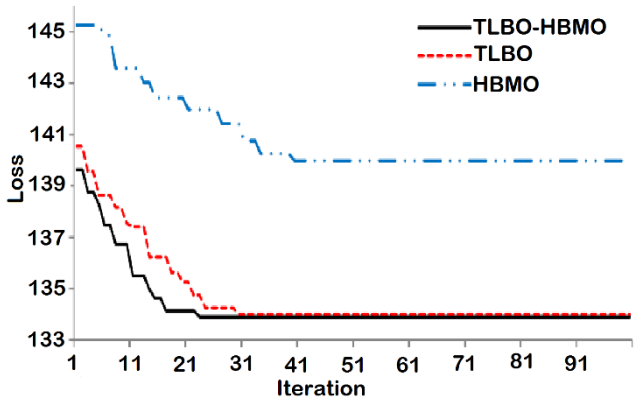


Fig 23: Convergence plot for loss with the different optimization algorithms.

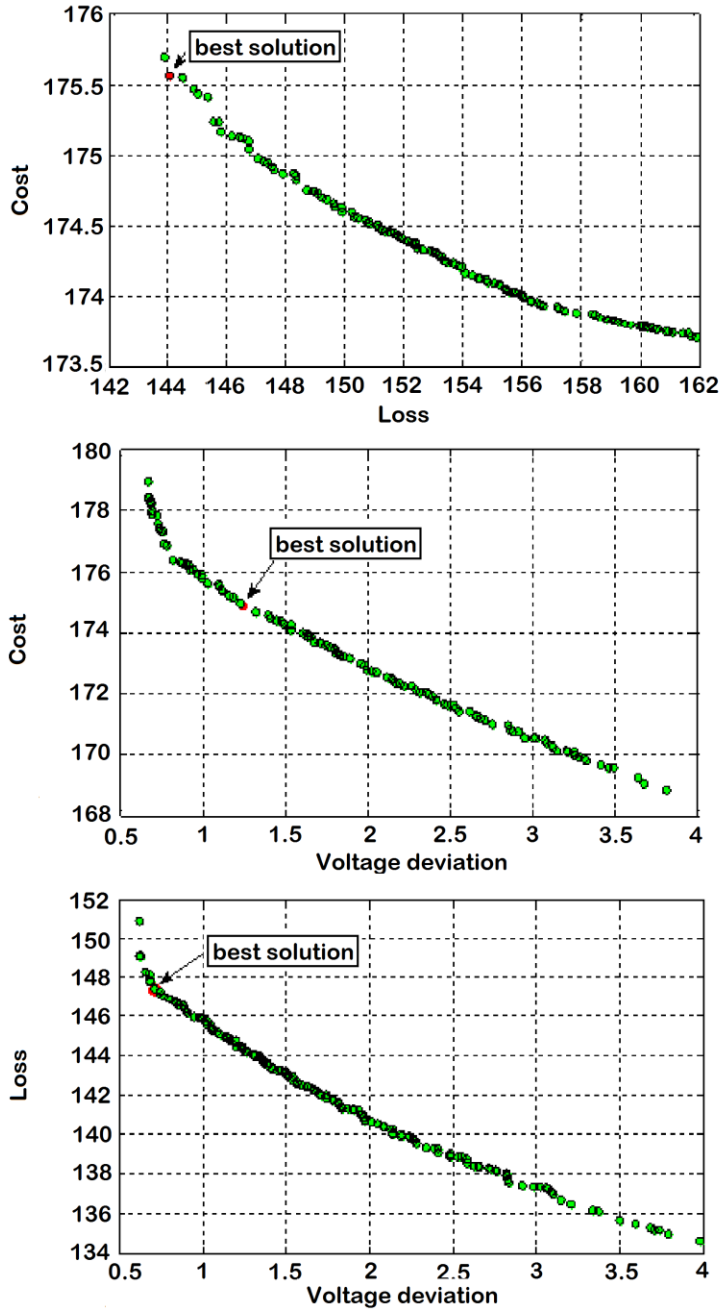


6.1.2 Multi-objective optimization

We have presented the multiobjective optimization in this section. In this regard, we have determined the results by using the Pareto optimal solution concept. These results are essential for decision-makers who have the same objective functions to find the effects of objective functions on each other. Therefore, we have obtained the Pareto optimal solutions in this section.

To assess the effects of the objective function on each other, we have considered seven cases. We have kept the first three cases for single-objective optimization problem and the others for multiobjective problem. The issues are as follows:

Fig 24: Pareto front of the proposed algorithm for two objective functions.

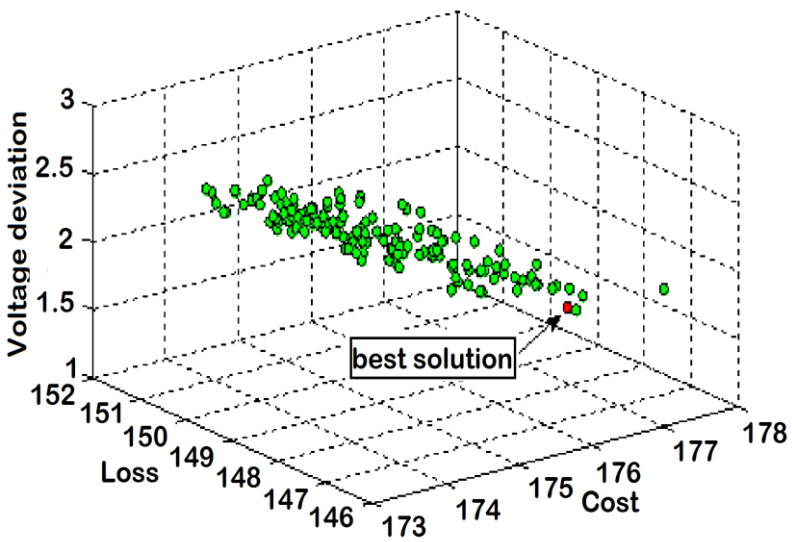


- Case I, II, and III: single objective function (i.e., cost, loss, and voltage deviation, respectively).
- Case IV: multi-objective function (i.e., loss and cost functions).
- Case V: multi-objective function (i.e., voltage deviation and cost functions).

- Case VI: multi-objective function (i.e., voltage deviation and loss functions).
- Case VII: multi-objective function (i.e., all objective functions).

We had shown the results of the first three cases in the single-objective section of this scenario. We have demonstrated the effects of IV, V, and VI products with two objective functions in Fig. 24. This figure depicts the Pareto front of each two objectives together. We have shown the Pareto front of three objective functions (i.e., case VII) in Fig 25.

Fig 25: Pareto front of the proposed algorithm for three objective functions.



Analysis of Fig 24 and Fig 25 shows that each Pareto optimal set has 150 non-dominated solutions. The best solution that is selected in these figures are the solutions with minimum results in the single objective approach. The diversity of the non-dominated solutions over the Pareto optimal front offers the proposed optimization algorithm's ability to find feasible solutions. The decision-maker can select each of the Pareto optimal solutions as the final solution. This selection can be made by using the best-compromised solution concept. In this regard, we have applied the goal attainment optimization (GAO) approach to select the best-compromised solution. We should consider the importance of the objective functions for decision-makers in the GAO process. In this regard, we have considered ω_i that shows the importance of the objective function, such that $\sum_{i=1}^{3} \omega_i = 1$.

We have shown the GAO process results in Table 1. This table only considers some decision-maker preference combinations by using ω_i. These ω_i (i.e., objective function weights) are not all possible combinations; we have solely presented the conventional consequences as different cases in this table (i.e., cases IV to VII). We have kept the first three cases for single objective results (i.e., without objective function weights). We have analyzed this table as follow:

– Case I, II, and III show the conflic of objective functions somehow that minimizing cost leads to increasing loss drastically, minimizing loss leads to increasing voltage deviation excessively, and minimizing voltage deviation leads to increasing cost radically.

– by comparing the first part of cases IV and V, we can find out the cost function of case IV is more than that of case V. It means that the loss function has more effects on the cost function than the voltage deviation function.

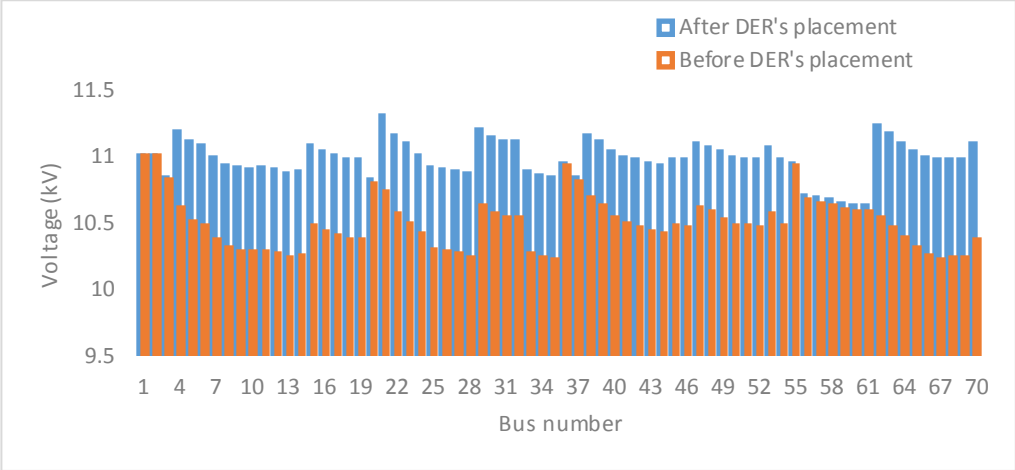
– Case VII shows the results of implementing three sets of weight factors. When checking the loss function in three parts of VII, we can determine the loss function of the second part of VII ($\omega_i = 0.2$) is less than the first part of VII ($\omega_i = 0.4$). It means that the loss function has a conflict with the other objective functions.

Table 19: proposed algorithm results in all cases with different weights for choosing objective functions to show objective functions effectiveness.

Cases	ω_1	ω_2	ω_3	Cost ($)	Loss (kWh)	Voltage deviation (pu)
Case I	_	_	_	168.6734	166.2054	3.7919
Case II	_	_	_	172.0434	133.8983	4.0903
Case III	_	_	_	180.6717	151.9953	0.5920
	0.5	0.5	0	175.5599	144.0500	_
Case IV	0.75	0.25	0	174.7536	148.7010	_
	0.25	0.75	0	175.6926	143.8788	_
	0.5	0	0.5	174.8915	_	1.2429
Case V	0.75	0	0.25	168.8420	_	3.8103
	0.25	0	0.75	176.3768	_	0.8156
	0	0.5	0.5	_	147.4056	0.7104
Case VI	0	0.75	0.25	_	137.5584	2.8314
	0	0.25	0.75	_	149.1343	0.6241
	0.33	0.33	0.33	174.5653	144.2806	2.4789
Case VII	0.2	0.4	0.4	175.7506	148.6220	1.7759
	0.4	0.2	0.4	173.2200	146.0133	1.7412
	0.4	0.4	0.2	171.1295	143.3625	3.8814

We have shown the DERs placement effects on voltage profile in Fig 26. This figure shows the voltage profile before and after the DERs placement in case VII-III.

Fig 26: Voltage profile comparison before and after the DER placement.



The results prove the superiority of the proposed hybrid optimization algorithm over the others it makes from those. Its authority is related to accuracy and calculation velocity in achieving the best solution on the given data-set. On the other hand, collecting the input data may be the only difficulty implementing the proposed hybrid algorithm.

The real-world examples of the proposed optimization problem can complete the importance of the proposed optimization algorithm. Firstly, the electric utility (i.e., Tavanir-Bargh-Mantaghei-Ostan-Fars) of Shiraz, a city located in Iran, has presented some third-part-centric projects [83,84] to implement DERs units on the Shiraz distribution system. These projects have been defined as improving the distribution system's voltage profile and investors' interest in installing DER units. The proposed optimization algorithm can help the electric utility determine the DERs' best locations to use in the investors' tender documents in these projects. Based on the tender documents, the third-part company would suggest a price for the project in an auction market held by Moshaver-Fars-Co, a sub-utility company. Secondly, there is a scenario of Utility-Centric in the Egyptian power system [85]. The electric utility can determine the DERs' best locations and sizes with the proposed optimization algorithm in this project. In this project, the objective function is the voltage profile optimizing.

6.1.3 Overview conclusions

We designed a new multiobjective hybrid optimization algorithm for DERs placement and sizing in the 70-bus test system. Moreover, we added some limitations to the optimization problem to make it more realistic, including calculation of hosting capacity of the distribution system and former installed DERs effects. These restrictions cause that we needed to more accurate optimization algorithm than the proposed optimization algorithm of this thesis second scenario. The results proved the capability and performance of the proposed hybrid optimization algorithm. We obtained GAO process results to help decision-makers find the best match optimal solution to the specific projects.

6.2 Simulation Results of the fourth scenario

For the fourth scenario, firstly, we have presented requirements and inputs for implementing and simulating the proposed optimization algorithm in the proposed system. Then, we have described the simulation results in this section.

6.2.1 Input data for simulation

The fourth scenario has investigated the optimal DERs, microgrids, and ESSs dispatch on a VPP. The objective functions of this scenario contain annual cost and emission. Therefore, considering the other objective functions such as the voltage deviation and loss can investigate in future research.

We have considered the following components for VPP:

- Photovoltaic unit (maximum capacity equals 557 kW)
- Wind turbine (maximum capacity equals 6 kW)
- ESS (we have considered 1MW (1MWh) Lead Acid battery as an example)
- Diesel generator maximum capacity for total diesel generators equals 2.1 GW (we have considered one 0.1 MW and two 1 MW diesel generators)
- Converter

- Local controller for each component
- An energy management system
- Distribution system

Although we did not consider other potential components for designing the VPP, the proposed optimization algorithm and methodology can be used to apply other projects.

We have considered the input of the introduced models in section 3 are central estimates of US generators' energy prices and capital, operating, and maintenance costs. We have considered the island mode for the microgrid operation. To meeting electricity demand, wind turbines cannot contribute. Therefore, the wind turbine capacity credit decreases to about zero within the microgrid.

The last step of this scenario is sensitivity analysis. We have performed the sensitivity analysis on the results of the central estimate by varying the energy prices. In this regard, we have considered two cases for altering the gas price and electricity price, and then we have applied the proposed approach to each case.

To implement the proposed optimization algorithm, we have considered a real-world VPP system. We have shown this VPP system in Fig. 27. This figure shows the VPP contains:

- A wind turbine.
- A photovoltaic unit.
- Two diesel generators.
- An ESS.
- A microgrid having a diesel generator and a wind turbine.

Fig. 27 The proposed virtual power plant simulated in HOMER software

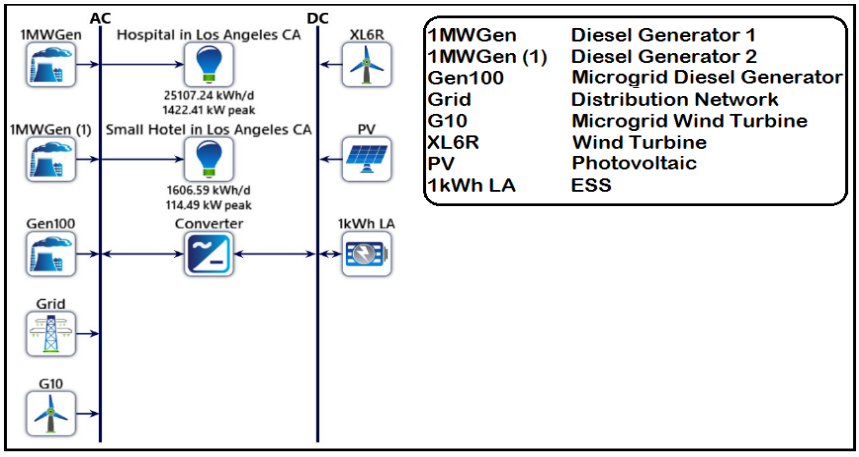


Fig. Ref: [52].

We have shown the two loads power profile in the VPP system in Table 20 and Fig. 28. Moreover, we have demonstrated the specification of other existing units in the VPP in Table . The data of these tables and figures are collected based on reality.

Fig. 28 A small hotel power profile for 12 months in Los Angeles, CA

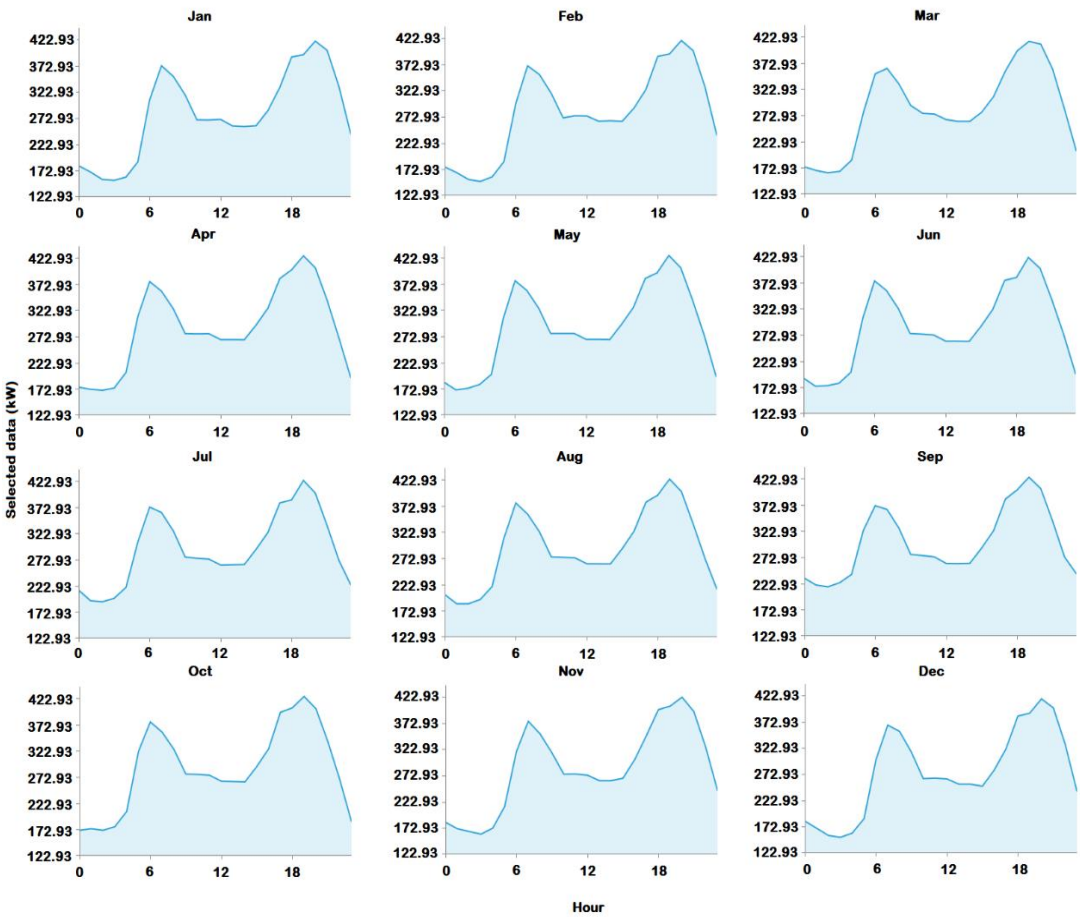


Fig. Ref: [52].

Table 20 A hospital power profile data for 12 months in Los Angeles, CA

Hour	January (kW)	February (kW)	March (kW)	April (kW)	May (kW)	June (kW)	July (kW)	August (kW)	September (kW)	October (kW)	November (kW)	December (kW)
0	866.43	865.55	875.57	868.64	850.28	806.77	788.22	774.33	781.36	823.79	859.8	868.3
1	859.86	860.24	870.84	867.58	850.7	807.4	787.37	775.67	781.61	826.39	862.68	866.02
2	856.53	853.41	867.23	866.5	852.37	810.97	786.88	777.8	782.69	830.35	863.5	863.94
3	854.68	852.81	927.15	958.29	941.4	904.17	875.37	871.81	871.81	871.89	920.28	874.09
4	937.61	935.53	956.95	958.29	939.75	901.43	876.22	874.59	875.18	922.37	952.99	939.73
5	937.75	934.91	1111.4	1176.34	1145.57	1117	1084.06	1089.55	1090.27	1142.96	974.4	940.92
6	1162.23	1152.1	1258.36	1291.51	1256.68	1235.47	1201.37	1209.56	1195.76	1244.64	1177.52	1154.71
7	1269.44	1262.85	1324.49	1327.75	1291.91	1269.16	1245.43	1252.32	1237.31	1276.29	1279.72	1257.59
8	1315.4	1305.07	1358.95	1352.72	1315.17	1294.48	1276.01	1289.17	1272.46	1293.22	1311.82	1306.3
9	1343.65	1330.64	1370.33	1350.58	1314.38	1293.49	1284.46	1299.98	1285.01	1293.2	1328.22	1336.72
10	1341.98	1330.33	1366.02	1346.37	1308.32	1291.23	1283.48	1303.3	1291.01	1289	1324.67	1329.11
11	1337.92	1325.43	1330.72	1304.27	1266.56	1248.71	1243.69	1262.8	1252.73	1254.47	1315.96	1322.29
12	1293.5	1286.3	1339.35	1336.87	1296.56	1282.81	1277.09	1297.73	1284.19	1278.57	1279.93	1272.09
13	1319.39	1316.86	1350.37	1336.29	1296.33	1284.77	1278.46	1299.71	1284.62	1279.24	1308.11	1300.7
14	1318.88	1319.98	1352.84	1339.36	1297.27	1288.54	1279.47	1304.31	1285.67	1281.34	1309.28	1303.64
15	1322.33	1324.79	1361.91	1351.88	1304.34	1297.98	1287.8	1316.91	1293.77	1285.74	1314.32	1311.35
16	1338.57	1337.17	1371.73	1357.7	1305.33	1300.46	1289.32	1320.34	1296.85	1285.8	1331.35	1332.17
17	1360.02	1351.33	1197.66	1100.59	1059.69	1019.15	1003.14	1011.53	1006.4	1037.75	1321.77	1344.07
18	1107.52	1106.39	1125.39	1110.08	1075.27	1021.83	1004.73	1012.09	1009.05	1041.29	1087.89	1101.34
19	1103.52	1100.4	1032.35	979.43	958.89	910.59	894.63	887.02	881.7	915.59	1072.97	1097.66
20	976.48	970.65	962.41	940.29	920.46	878.7	859.52	849.94	846.5	879.99	855.53	977.42
21	939.57	935.93	904.23	873.39	853.95	814.68	793.86	782.92	783.01	816.01	918.46	944.5
22	877.21	874.5	883.69	874.91	855.14	815.46	794.51	782.4	786.13	819.05	867.72	883.23
23	878.57	877.69	878.81	864.1	844.37	803.22	783.36	770.43	777.43	813.22	971.22	882.86

Table Ref:[52].

Table 21 Size and model of generators and storages used in the virtual power plant

Component	Model	size
Generator1	Diesel fixed capacity Genset	1MW
Generator2	Diesel fixed capacity Genset	1MW
Generator3	Diesel fixed capacity Genset	100kW
PV	flat plate	557kW
Storage1	Lead Acid	1kWh

WT1	Generic	10 kW
WT 2	Bergey Excel 6-R	6kW

Table Ref:[52].

6.2.2 Simulation Results

We have presented a hybrid optimization algorithm to optimize annual cost and emission functions throughout a VPP practical model. We have implemented the proposed VPP system in HOMER software, and we have obtained 57,173 solutions, including 51,908 feasible solutions and 5,265 infeasible solutions. We have described the three most effective solutions for most of the decision-makers as follows:

- First solution: This solution has considered electricity generation participants are all installed components.
- Second solution: This solution has minimized the investing cost by considering the minimum number of the mentioned components.
- Third solution: This solution has minimized the operation cost.

We have shown the results for the first solution in Table 2. This table shows the maximum total cost and operating cost belong to Generator 1. Moreover, we have demonstrated the generators' productions in Table 2. This table compares the electricity generation of all components. As the wind and sunlight are free resources, we have considered the resource cost of wind turbines and zero photovoltaic units. Moreover, we have considered zero replacement cost for PV and Generator 3 because having more than 25 years of replacement is more than the considered period in this research.

Table 22. Annual cost and net present for the first solution

Component	Capital cost ($)		Operating cost ($)		Replacement cost ($)		Salvage cost ($)		Resource cost ($)		Total cost ($)	
	Net present	annual	Net present	annual	Net present	annual	Net present	annual	Net present	annual	Net present	annual
Generator1	300,000	13,476	1.95M	87,600	3.74M	168,211	-95,604	-4,295	22.7M	1.02M	28.6M	1.29M
Generator2	300,000	13,476	276,260	12,410	509,594	22,892	-222,678	-10,003	1.58M	71,086	2.45M	109,861
Generator3	40,000	1,797	15,271	686.00	0	0	-613.18	-937.67	52,256	2,347	93,877	4,217
PV (flat plate)	1.57M	70,314	139,379	6,261	0	0	0	0	0	0	1.70	76,575
Wind turbines	10,000	449.21	2,226	100.00	8,338	374.53	-5,975	-268.42	0	0	14,588	655.33

Table Ref:[52].

Table 23 Electricity generation percentage and the amount for the first solution

Component	Production (kWh/yr)	Percent
Generator1	5,136,185	51.5
Generator2	298,575	3.00
Generator3	5,297	0.0532
PV (flat plate)	1,033,097	10.4
Wind turbine1	9,589	0.0962
Wind turbine2	9,304	0.0934
Grid Purchases	3,472,028	34.8
Total	9,964,076	100

Table Ref:[52].

We have presented a brief analysis of the applied renewable generators in the first solution in Table 24. This table shows the renewable generators' participation in generating electricity. Besides, this table presents three types of results: energy generation types, electricity generation capacity, and power system peak values. This table's most important data is 43 percent participation of renewable generators in the peak time by applying the first solution.

Table 24 Summary of renewable generators for the first solution

Capacity-based metrics	Value
Nominal renewable capacity divided by total nominal capacity	21.4%
Usable renewable capacity divided by full capacity	18.0%
Energy-based metrics	Value
Complete renewable production split by load	10.8%
Renewable total output divided by generation	10.6%
One minus total non-renewable production divided by the load	44.2%
Peak values	Value
Renewable output divided by the whole generation	43.3%
One minus non-renewable output divided by the full load	31.6%

Table Ref:[52].

We have shown the results for the second solution in Table 25 and Table 2. These tables show the only generators are two diesel generators in the second solution. Analysis of data shows the minimum investing cost is about 600,000 $ for the first year while the power grid purchases are 35 percent.

Table 25 Annual cost and net present for the second solution

Component	Capital cost ($)		Operating cost ($)		Replacement cost ($)		Salvage cost ($)		Resource cost ($)		Total cost ($)	
	Net present	annual	Net present	annual	Net present	annual	Net present	annual	Net present	annual	Net present	annual
Generator1	300,000	13,476	1.95M	87,600	3.74M	168,211	-95,604	-4,295	24.1M	1.08M	30.0M	1.35M
Generator2	300,000	13,476	629,767	28,290	1.07M	47,855	-68,118	-3,060	4.17M	187,539	6.10M	274,101

Table Ref:[52].

Table 26 Electricity generation percentage and the amount for the second solution

Component	Production (kWh/yr)	Percent
Generator1	5,412,063	55.5
Generator2	862,485	8.85
Grid purchases	3,476,000	35.6
Total	9,750,548	100

Table Ref:[52].

We have shown the results for the third solution in Table 27 and Table 2. These tables show the minimum operating time while using maximum components. We have considered the accuracy tolerance 0.1 percentage in this thesis.

Table 27 Annual cost and net present for the third solution

Component	Capital cost ($)		Operating cost ($)		Replacement cost ($)		Salvage cost ($)		Resource cost ($)		Total cost ($)	
	Net present	annual	Net present	annual	Net present	annual	Net present	annual	Net present	annual	Net present	annual
Generator1	300,000	13,476	1.95M	87,600	3.74M	168,211	-95,604	-4,295	23.0M	1.03M	28.9M	1.30M
Generator2	300,000	13,476	258,451	11,610	266,754	11,983	-15,536	-697.89	1.49M	66,830	2.30M	103,201
Generator3	40,000	1,797	9,216	414.00	0	0	-20,874	-937.67	32,052	1,440	60,395	2,713
PV (flat plate)	1.57M	70,314	139,379	6,261	0	0	0	0	0	0	1.70	76,575
Wind turbine 2	10,000	449.21	2,226	100.00	8,338	374.53	-5,975	-268.42	0	0	14,588	655.33

Table Ref:[52].

Table 28 Electricity generation percentage and the amount for the third solution

Component	Production (kWh/yr)	Percent
Generator1	5,079,165	50.5
Generator2	317,241	3.16
Generator3	8,575	0.0853
PV (flat plate)	1,162,235	11.6
Wind turbine2	9,304	0.0926
Grid Purchases	3,471,812	34.6
Total	10,048,332	100

Table Ref:[52].

We have compared the cash flow of the presented solutions in Fig. 29 for 25 years period. For 25 years, we have shown the second solution has the lowest initial cost, and the third solution has the quietest operation time. The presented results are more significant for the VPP to find the optimal solution for the next 25 years.

Fig. 29 Cost comparison for the proposed solutions in 25 years

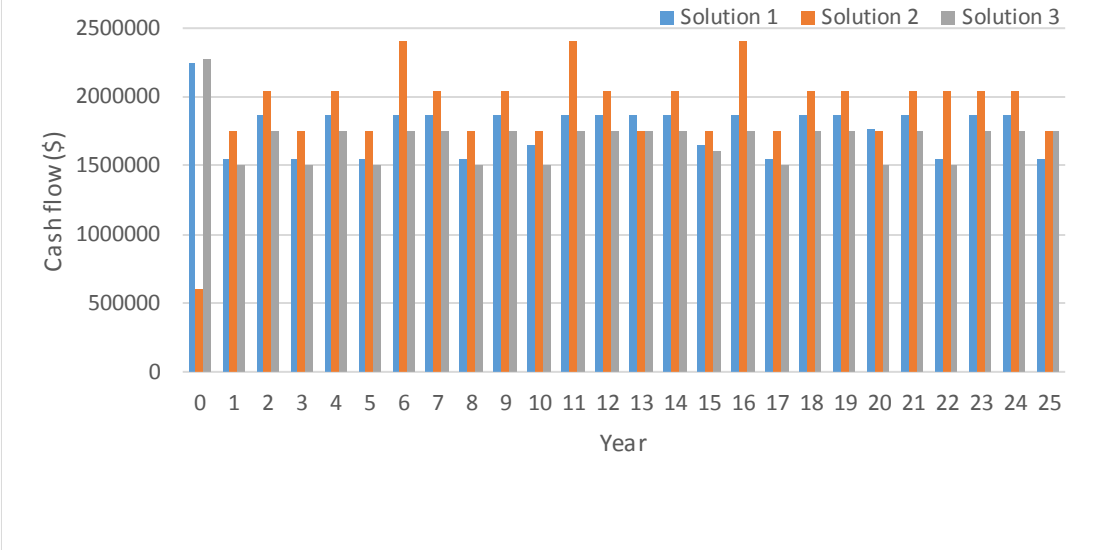


Fig. Ref:[52].

We have compared the proposed hybrid algorithm results with PSO and GA algorithms as the two best optimization algorithms in this field [86]. We have reached the suggested algorithm results of the third solution with the mentioned optimization algorithms. This comparison is shown in Fig. 30. This figure depicts the superiority of the proposed optimization algorithm in accuracy and calculation velocity.

Fig. 30 Convergence comparison of optimization algorithms for two objective-functions: A: Annual cost and B: emission

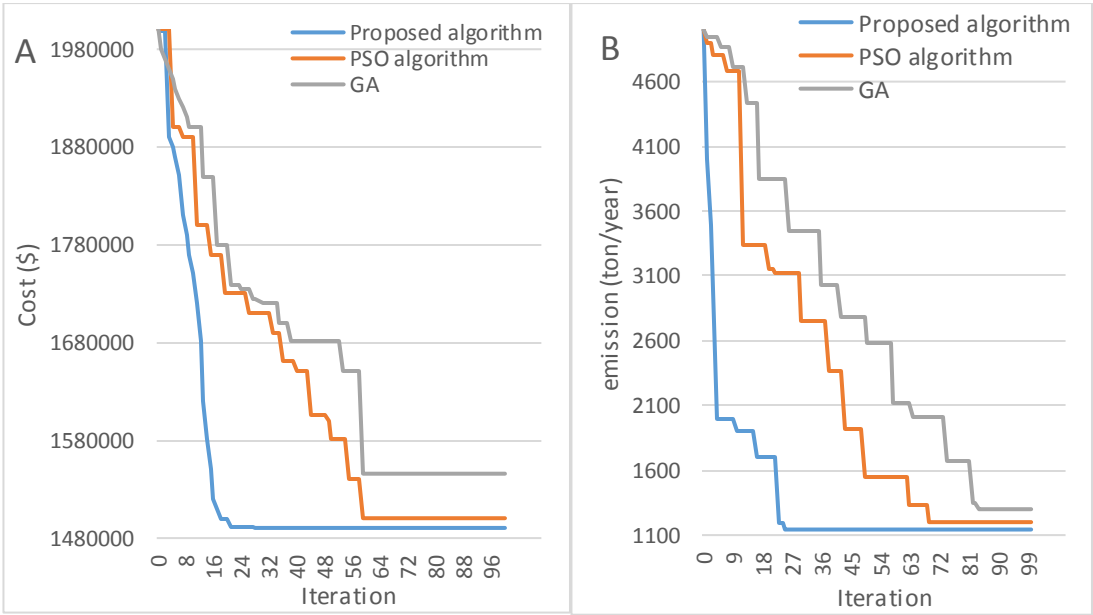


Fig. Ref:[52].

We have calculated the total net present cost (NPC) for the proposed solutions (i.e., NPC= (is the present value of all the costs the system incurs over its lifetime) - (the present value of all the revenue it earns over its lifetime)). The NPC of the first, second and third solutions are $40,934,530.00, 43,833,920.00, and 40,721,800.00, respectively.

6.2.3 Overview conclusions

We presented a new hybrid optimization algorithm for finding the optimal DERs dispatch to schedule a VPP. We have discussed the three most effective solutions for electric utilities (i.e., decision-makers). We have shown all the annual costs during 25 years. The most notable points are as follows:

- The first solution offers about 43% renewable energy resources participation.
- The third solution shows the best economical solution but its investment cost is more than the others.
- The second solution offers the best investment cost.

6.3 Chapter considerations

This chapter presented two new hybrid optimization algorithms to implement on two different platforms, including a 70-bus distribution system and a VPP system. Each design was an energy management scenario for integrating DERs. The performance of both optimization algorithms and the best-reported optimization algorithms shows their superiority in accuracy and calculation velocity. Therefore, the proposed optimization algorithm are the best ones for the proposed energy management scenarios.

7 GENERAL CONCLUSIONS AND PERSPECTIVE FOR FUTURE RESEARCH

7.1 General conclusions

This thesis has presented the different scenarios for the optimization of the power distribution system for applying renewable energy resources. Each scenario may be useful for a specific project. The developer of the distribution system (power utility company or decision-maker) can select the best design that matches the objectives of improvements considered for the distribution system. For each scenario, the best optimization algorithm and the best optimal solutions were introduced.

The first scenario is suitable for Utilities that have a single-objective for placement and sizing of DER. They can use the proposed optimization algorithm to optimize the objective function with the best accuracy and calculation velocity. The second scenario is perfect for Utilities that have multiobjective for placement and sizing of DER. The third scenario is appropriate for Utilities in that the distribution system hosting capacity and the effects of existing DER are essential for them. In this scenario, the best multiobjective optimization algorithm for solving the placement and sizing of DER is presented. Lastly, the final design is for distribution systems in which all buses may have installed DER. In this scenario, the DER placement problem has no meaning because all buses have DER. The optimization problem is finding the best working DER schedule in the distribution system that shows in the virtual power plant.

Different scenarios cover most developing and improvement projects of the power distribution system to apply renewable energy resources. In this regard, the best optimization algorithm and optimal solution are presented for each scenario. The superiority of each system proposed optimization algorithm results in accuracy and velocity compared to the other optimization algorithms.

7.1.1 The first scenario conclusions

This thesis presented a new modified TLBO algorithm for the single-objective DERs placement and sizing in the distribution system (i.e., the first scenario). The further modification improved the learning and teaching phases in the TLBO algorithm. The proposed optimization algorithm could minimize the objective functions, including cost, loss, and voltage deviation functions.

We presented the optimal DERs (i.e., fuel cell and micro-turbine) locations on a 70-bus test system. Finally, we compared the proposed optimization algorithm results with the original TLBO, HBMO, GA, and PSO algorithms. This comparison proved the proposed optimization algorithm superiority in accuracy and calculation velocity.

7.1.2 The second scenario conclusions

This thesis presented a new modified TLBO algorithm for the multiobjective DERs placement and sizing in the distribution system (i.e., the second scenario). The modification added a fuzzy decision-making tool to the TLBO algorithm to find Pareto optimal solutions. Then, a QOBL technique is connected to the TLBO algorithm to increase accuracy. The proposed optimization algorithm could correctly minimize the objective functions, including cost, loss, voltage deviation, and emission.

To find the proposed optimization algorithm capability, we implemented the proposed optimization algorithm in a 70-bus test system for finding the optimal DERs locations and sizes. The proposed optimization algorithm could find several Pareto optimal solutions. Lastly, we compared the results of GA, HBMO, and PSO with the proposed optimization algorithm; this comparison proved the accuracy and calculation velocity of the proposed optimization algorithm.

7.1.3 The third scenario conclusions

We presented a new hybrid optimization algorithm for the multiobjective placement and sizing of nineteen DERs in the distribution system, considering the distribution system hosting capacity and ten existing installed DERs. These

considerations made the DERs placement problem more realistic. We determined three objective functions, including cost, loss, and voltage deviation functions.

The proposed hybrid optimization algorithm could correctly minimize the objective functions in single-objective and multiobjective modes. We proved the single-objective results are significant in calculation velocity and accuracy, while the multiobjective results show several Pareto optimal solutions. Each of the Pareto optimal solutions can be a choice for electric utility (i.e., decision-maker) based on the project characteristics.

Moreover, we compared the proposed algorithm results with GA, PSO, TLBO, and HBMO algorithms that were more accurate and faster.

7.1.4 The fourth scenario conclusions

We presented the optimal dispatch of DERs, microgrids, ESSs for a VPP using a new hybrid optimization algorithm. We considered the uncertainty parameters of demand responses. We calculated all the feasible solutions, and we analyzed the most significant solutions (i.e., three solutions) for electric utilities (i.e., decision-makers). Moreover, we compared the results of these three solutions in 25 years. Based in the distribution system requirements, decision-makers can analyze and select the solutions presented. The first solution shows about 43% renewable energy resources participation, which was an interesting point because these renewables could help to peak shaving of voltage profile. The third solution delivers the best economic solution, but its investment is costlier than the others.

7.2 Prospective for future research

Future research can consider the Automatic Voltage Regulators' placement or some types of Flexible AC Transmission System (FACTS) devices or consider reconductoring to improve second and third scenarios. Most of these devices in the distribution system can improve some objective functions, such as the distribution system's voltage profile and losses.

Moreover, considering multi-objective optimization algorithms and finding the best one can improve the last scenario. This thesis's presented optimization algorithm was a single-objective optimization algorithm for the previous method (i.e., the fourth scenario). Thus, the next step can be considering a multi-objective optimization algorithm in the same platform.

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