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Review

Voltage Optimization in PV-Rich Distribution Networks—A Review

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Abstract: There is a rising trend to integrate different types of distributed generation (DG), especially photovoltaic (PV) systems, on the roofs of existing consumers, who then become prosumers. One of the prosumer impacts is voltage violations, which conventional strategies find hard to solve. However, some prosumers, such as those with PV with inverters in their configurations, can actively participate in voltage optimization. To help find the optimal PV inverter setting with the objective of voltage optimization, an optimal power flow (OPF) can be a promising and reliable tool. This paper tries to shed light on the complex problem of voltage optimization in distribution networks (DNs) with PV prosumers. Relevant scientific papers are analyzed and optimization characteristics such as objective functions, variables, and constraints are summarized. Special attention is given to the systematization and classification of papers according to the mathematical formulation of the optimization problem (linear, nonlinear, integer, etc.) and the applied solving methods. Both analytical and computational intelligence optimization methods as well as their advantages and limitations are considered. Papers are also categorized according to the distribution network model used for testing the developed solutions.

Keywords: active distribution networks; optimal power flow; prosumers; PV inverter volt/VAR optimization; review

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1. Introduction

The participation of renewable energy sources (RESs), battery storage systems, and other flexible loads, commonly referred to as prosumers, changes the character of distribution networks (DNs) from passive to active. For this reason, both generating units and loads are included in the determination of power flow and voltage profile. The nature of prosumers is unpredictable and intermittent, so existing DNs are not adapted to their influence. This is particularly evident in frequent voltage violations [1]. A voltage rise is addressed as a major issue caused by prosumers and impacts DNs [2]. The distribution system operator (DSO) is responsible for maintaining voltage within the allowable limits for the secure operation of DNs [3]. However, voltage control mechanisms that were once applicable in passive DNs become less valid and new mechanisms are required [4–6].

While DG can cause voltage violation in the DN, the same DG can help solve the problem of voltage violation, for example by managing active or reactive power. This problem/solution principle is especially interesting in the case of reactive power management [7]. When it comes to RESs in DNs, the main representative is a photovoltaic (PV) system [8,9]. Traditionally, most DSOs require PVs to operate with the unit or fixed power factor [1]. PV inverters have several modes of operation, but volt–VAR control has become certainly significant for voltage optimization. A major advantage of using a PV inverter and volt–VAR control is that reactive power can be injected/absorbed even where there is no production. Since prosumers contribute to the complexity and unpredictability of such DNs, it is crucial to use optimization methods and analyzed software tools that allow DN monitoring and finding suitable and optimal set points for PV inverters. In addition, optimal power flow (OPF) has proven to be an efficient tool for the operation of active DNs. In order to illustrate the problem/solution principle of PV inverters, a case study is developed in this paper presenting the low voltage DN with the connected PVs. Different power flow simulations are presented and they include:

- the situation when PVs production is maximal and voltage rise along the feeder is present;
- the situation when PV inverters inject reactive power.

Nowadays, optimal management of active DNs represents an attractive topic, and a large and growing body of literature focuses on this topic. Some related reviews on the optimization DNs are listed in Table 1. Refs. [10,11] show the impact of PV on DNs, the related problems, and possible solutions. Refs. [12–14] study voltage violation mitigation and voltage control strategies. Ref. [12] deals with voltage control methods in DNs with PVs and their advantages and disadvantages. In addition to [12], a comprehensive review of voltage control methods is given in [13]. In [14], voltage control models and methods are divided according to the communication strategy. The application of OPF in DNs is discussed in [15,16]. The researchers in [15] address a probabilistic approach to solving OPF in active DN. The authors in [16] study OPF in smart DNs and microgrids according to objectives, methods, and future challenges.

Table 1. Related review papers on the optimization of DNs.

Review Paper	Year	Focused Topics	Prosumer	Notes
[10]	2016	Impact of distributed generation (DG) on voltage control on DNs	Yes	Reviewed voltage control with DG with a focus on smart network technologies—demand side management (DSM) and energy storage systems (ESS)
[11]	2016	PV impact on DNs including voltage regulation issues, harmonic, and islanding operation	Yes	Reviewed issues caused by PV penetration in DN insight voltage regulation, harmonic, and islanding operation, and proposed technical solution
[14]	2017	Distributed and decentralized voltage control in smart DNs	Yes	Reviewed smart DNs according to communication systems, control models, and methods
[16]	2017	Application of OPF in smart DNs and microgrids	Yes	Reviewed OPF according to objectives, constraints, methods, and challenges
[12]	2018	Mitigation methods for voltage regulation in DNs with PV	Yes	Discussed ESS strategies, active power curtailment-based strategies, and reactive power control strategies
[13]	2020	Mitigation methods for voltage violation in DNs with PV systems	Yes	Presented different mitigation methods for voltage regulation in DNs and their merits and shortcomings
[15]	2022	Probabilistic OPF in active DNs	Yes	Scientometric review of OPF in active DNs—characteristics and challenges

While refs. [15,16] present interesting and useful reviews of OPF application to modern DNs, they are mainly focused on active power objectives [16] and probabilistic OPF [15]. So far, the research gap is present in the area of voltage optimization objectives in the case of using PV inverters for reactive power management. The problem/solution principle of using PV inverter reactive power for voltage mitigation motivated the authors of this paper to focus their review on scientific papers that applies OPF for voltage optimization in the DN using PV inverter reactive powers. The contributions of this review paper are:

1. Summary and classification of OPF objectives and variables in the case of voltage optimization in the DNs using PVs reactive power.

2. Comparison of the used mathematical formulations of the OPFs and their connections to analytical or computational intelligence solution methods.
3. Review of the different DN examples that are used for testing the developed optimization solutions.

This paper aims to provide the readers with starting points for OPF applications in PV-rich DNs and, in some way, to compare with conventional OPF. Therefore, the authors searched several bibliographical databases—IEEE Xplore, ScienceDirect, and MDPI.

The paper is structured as follows: Section 2 gives a prosumer definition, describes the voltage control capabilities of PV inverter, and presents the case study that illustrates the impact of PVs on the DN voltages. Section 3 addresses OPF in PV-rich DN—objectives and variables. OPF formulation and solution methods are discussed in Section 4. Test network models used in the literature are presented in Section 4. Conclusions with a note on future research are given in Section 5.

2. PV Prosumers in Distribution Network

In this section, various definitions and configurations of prosumers are presented. Then, the focus is on PVs and their voltage control capabilities. Finally, theoretical foundations are supported by the case study in which the part of the low voltage DN is presented and various cases are simulated.

2.1. Prosumer Definition and Configuration

Historically, the term "prosumer" was first mentioned in 1980 in Alvin Toffler's book *The Third Wave* [17]. In this book, the author discusses the transition of society from an Industrial Era in which production and consumption were separated to the Information Era. In this new concept of society, the term prosumer is created by combining a producer and a consumer. Nowadays, with the increase of integration of PVs in DNs, the notion of prosumer and prosumerism has become increasingly significant in electrical engineering [18]. Therefore, many authors propose the definition of a prosumer. The authors in [19–21] define a prosumer as an end-user that consumes electrical energy, acts as an energy producer, and shares surplus energy with utility networks and other consumers. In [22], prosumers are described as energy consumers or energy producers in different periods depending on their electricity demand and price. The focus is on the prosumer that only generates electricity. In [23,24], the authors include a facility for electricity generation and energy storage systems in the prosumer definition. The definition of prosumer was expanded in [25,26] and includes consumers that generate electricity and/or contain in their configuration home energy management systems (EMS), ESS, electric vehicles (EVs), and electric vehicle-to-grid (V2G) systems. In [27], a prosumer has been deemed as a consumer or an electricity producer and can be actively managed.

The European Union defined an active consumer uniform in its 2016 directive [28]. According to [28,29], an active consumer is "a customer or a group of jointly acting customers who consume, store or sell electricity generated on their premises, including through aggregators, or participate in demand response or energy efficiency schemes provided that these activities do not constitute their primary commercial or professional activity".

While a variety of definitions of the term prosumer have been suggested, this paper uses the following definition: a prosumer is an entity that not only withdraws/retracts energy from a network but also produces energy that can be consumed, stored or sold to the network and other consumers and actively participates in providing more flexibility such as voltage and reactive power control.

Prosumer configuration and interconnection with DN is shown in Figure 1. The main representative of distributed generation is the PV system. It often includes an ESS such as a battery in its configuration and together forms a hybrid system. EVs, electric V2G vehicles, smart home EMS, and other flexible loads represent demand-side management (DSM).

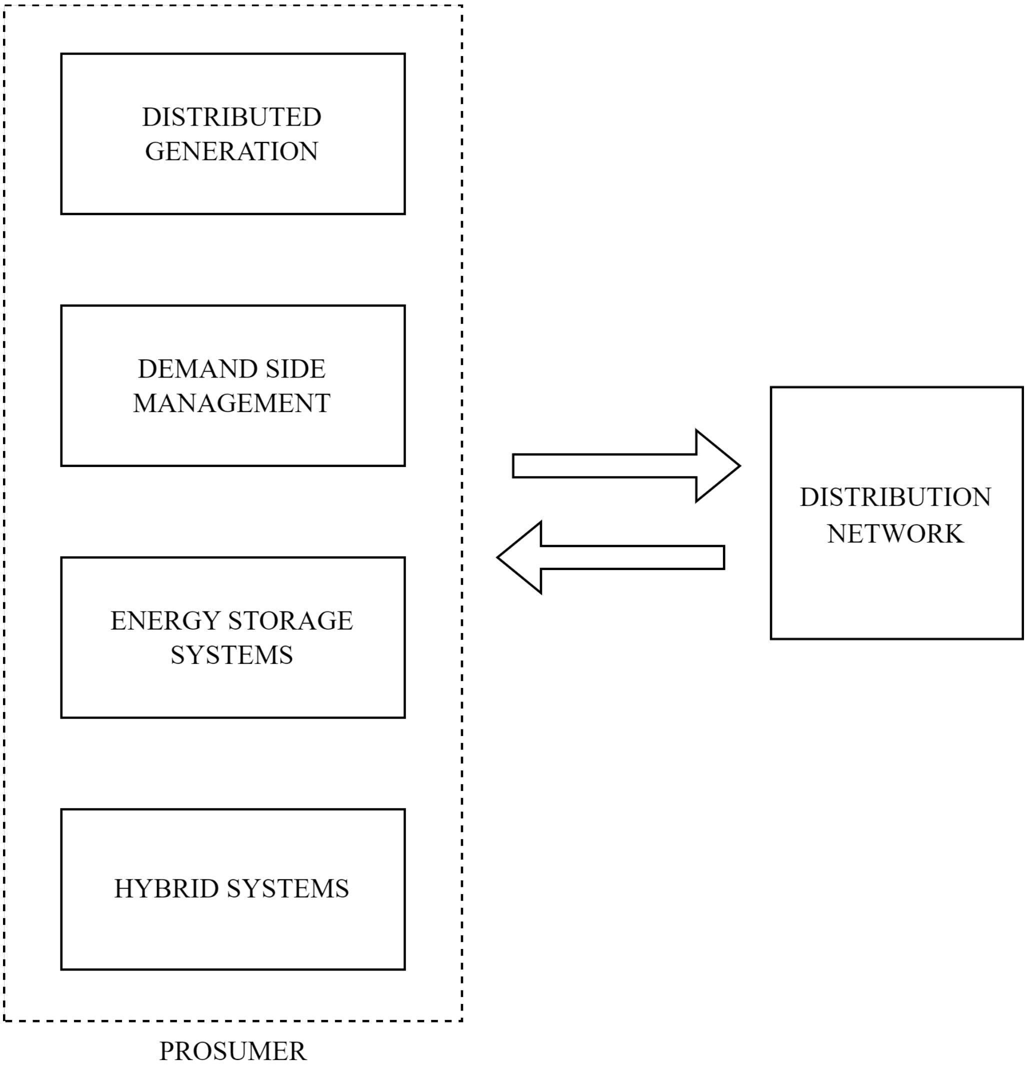


Figure 1. Prosumer configuration and interconnection with DNs.

2.2. PV System Capabilities for Voltage Optimization

This paper deals with PV prosumers with reactive power capability, i.e., other prosumer types are not considered. DSOs have the main responsibility for voltage optimization in DNs. Traditionally, the available variables are limited to the capacitor bank placement, tap changing transformer, network reconfiguration, cross-section enhancement, etc. However, some researchers [30,31] suggest that the aforementioned strategies may not be effective for prosumer-based DNs due to their slow response. The application of PV inverters represents a promising solution and in combination with already present control mechanisms can give results, so several studies have proposed their use for voltage optimization [32–36]. Different modes of operation are possible for PV inverters and the authors of [30] distinguish the following:

- fixed power factor mode;
- volt–VAR control;
- volt–watt control;
- mode for power rate limit;
- voltage balance mode.

In the fixed power factor mode, the power factor is maintained at a constant value and thus voltages are directly affected. Voltage control in the volt–watt control mode is achieved by active power from PVs. In the power rate limit mode, the rate of active power output from the PV inverter is limited. In volt–VAR control, reactive power from the PV inverter is used for voltage optimization. The general operating principle of volt–VAR control is described using a volt–VAR curve shown in Figure 2 [37]. The volt–VAR curve represents a relation between a voltage value at the point of common coupling (PCC) and reactive power from the PV inverter. If the voltage value on PCC is lower than the specific threshold, the PV inverter injects reactive power. On the other hand, in the case of the higher voltage value on PCC, reactive power is absorbed.

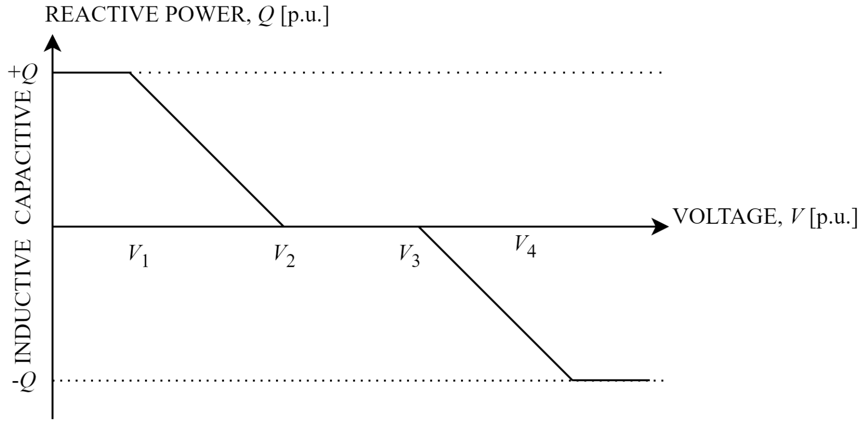


Figure 2. Volt–VAR curve of the PV inverter. Inductive reactive power reduces voltage value while capacitive reactive power increases the voltage value.

Reactive power capability determines the amount of reactive power available from the inverter [38]. Figure 3 represents reactive power capability determined with vectors of apparent power S and active power P [8,38,39]. The reactive power of the PV inverter depends on the active power and can be determined as:

$$Q_1^2 \leq \sqrt{S_1^2 - P_1^2} \tag{1}$$

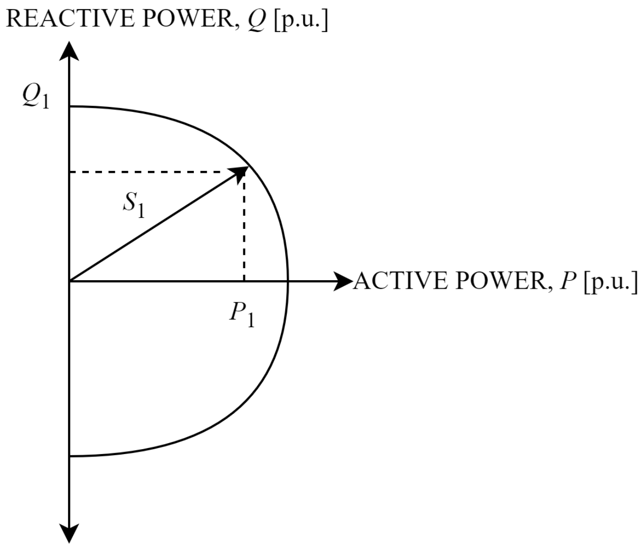


Figure 3. Power capability curve of PV inverter.

2.3. PV Inverter Impact on Distribution Feeder Voltage Profile

To provide a better insight into the voltage problem in DN caused by PVs, a case study is carried out. Two PV inverter control modes are chosen to clarify its capabilities for voltage optimization. The DN model, presented in Figure 4 [40], consists of three radial feeders supplied by a 10/0.4 kV substation. Each feeder supplies 20 residential consumers. More information about the network model can be found in [40]. It is assumed that half of the residential consumers have PV systems on their rooftops. The nominal power of each PV plant is 5 kW. The case studied in the simulations corresponds to maximum production and consumption of 0.2 kW with an inductive power factor of 0.9.

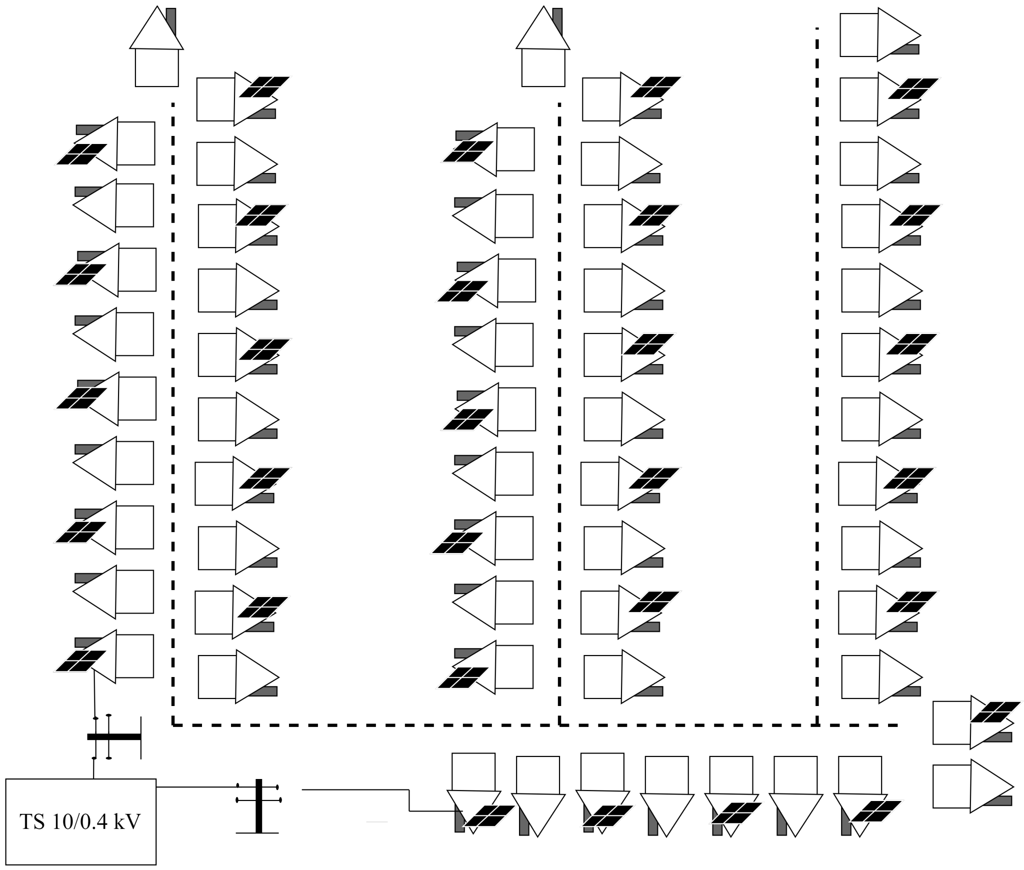


Figure 4. Model of DN used in the case study.

DIgSILENT PowerFactory [41] software is used for case study implementation and the conventional power flow is analyzed. Two modes of PV inverter operation are used in simulations: fixed power factor mode and volt–VAR control mode. The results for the fixed power factor mode are presented in Figure 5. The power factor range is taken from a real-life example of an inverter [42]. The voltage profiles at different power factor values are compared. There is an increase in the voltage profile at the unit power factor. The voltage profile is corrected by changing the power factor.

The comparison of voltage profiles at the unit power factor and the applied volt–VAR control mode is shown in Figure 6. In the case without voltage control (unit power factor), there is a voltage rise in the distribution feeder caused by PVs. The voltage values are in the range of 1.005 p.u. to 1.05 p.u. In the volt–VAR control mode, the voltage values are lower than the unit power factor and are in the narrower range of 0.992 p.u. to 1.005 p.u. These values are more acceptable for the operation of DN, i.e., voltage deviation is smaller.

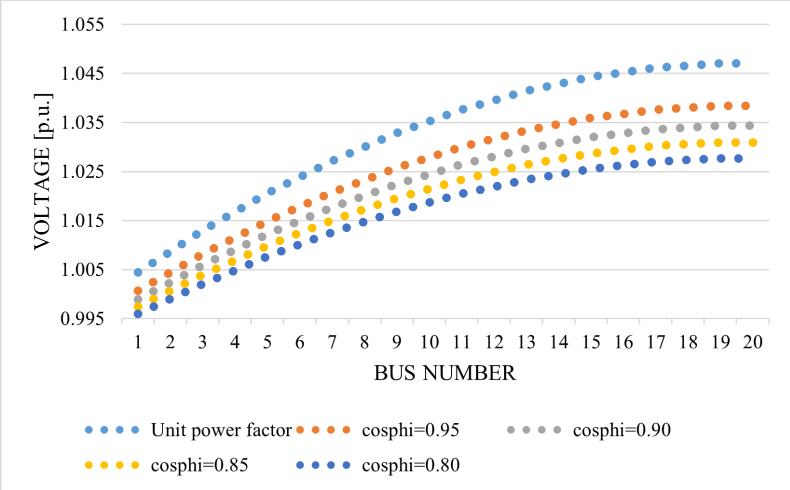


Figure 5. Voltage profile in a distribution feeder obtained using the fixed power factor control mode.

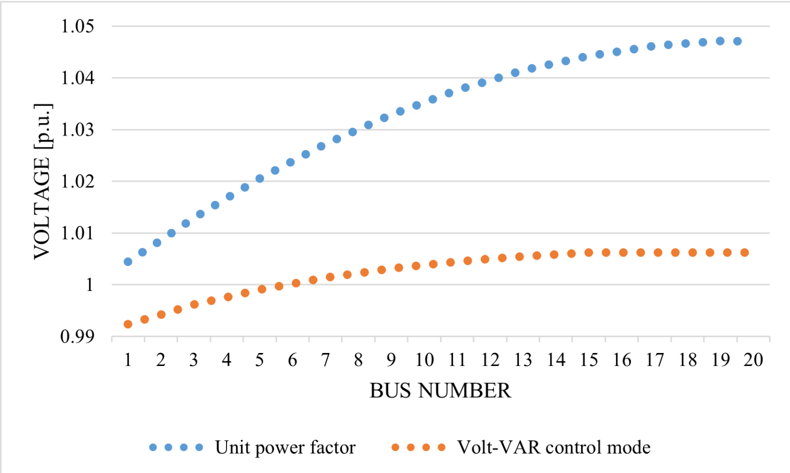


Figure 6. Voltage profile in the distribution feeder obtained using the volt–VAR control mode.

The obtained results show an improvement in the voltage profile of DN compared to the case without voltage control (unit power factor of the PV inverter). Voltage control in PV prosumer-rich DNs has a positive impact. The case study shows the possibilities of PV inverters regarding voltage control and the situation when there are lots of inverters placed at different positions in the DN. Determining the optimal operating point of the PV inverters imposes using optimization algorithms from which the OPF are imposed as a logical solution.

3. Voltage Optimization in PV-Rich Distribution Networks—Objectives and Variables

The OPF concept was proposed in the early 1960s [43] as an enhancement of economic dispatch to find the optimal solution for controlling variable settings under different constraints. The OPF is used as a universal term for problems associated with network optimization [44–47]. The OPF is ordinarily modeled to the appliance on transmission level considering large generating units. Besides the fundamental variables, the OPF model may contain ancillary generation units and variables representing the other segments of the power system used for optimal operation.

The transmission network (TN) diverges from DN in topology, nature, electrical parameters, power flow values, and a number of control devices. Unlike TNs, DNs are inherently unbalanced and more complex [48]. The reason for the imbalance is that the DN supplies unequal single-phase loads and contains unequal conductor interspace of three-phase segments [49,50]. The *R*/*X* ratio is high in DNs and contributes to the complexity of control and optimization. In contrast, the *R/X* ratio is low for TNs. Compared to DNs, TNs have a few direct consumers. The simple control and a well-built communication system of TNs are the main reasons why OPF has applied only at the transmission level. The integration of DGs and flexible loads such as EVs makes OPF feasible in DN optimization. To incorporate unpredictable DG and to exploit the potential of flexible loads, OPF became imminent for DNs [51]. Although there is no official record in the literature of the beginning of the application of OPF in DNs, it can be said it started with the integration of different types of prosumers in DNs [48].

3.1. General Formulation—Objectives and Variables

The OPF problem can be described as minimizing the objective function while taking equality and inequality constraints into account [48]:

$$minF(\mathbf{x,u}) = 0 \tag{2}$$

$$g(\mathbf{x,u}) = 0 \tag{3}$$

$$h(\mathbf{x,u}) \leq 0 \tag{4}$$

where $F(\mathbf{x,u})$ represents the objective function and $g(\mathbf{x,u})$ represents nonlinear equality constraints i.e., power flow equations, $h(\mathbf{x,u})$ represents nonlinear inequality constraints. The vectors $\mathbf{x}$ and $\mathbf{u}$ present state variables, and control variables, respectively.

In [48], the generally used objectives for OPF formulation are given. It should be noted that the objectives and constraints must be modeled accurately to obtain a satisfactory solution.

Scientific papers are included in this review if at least one of the objectives is voltage optimization and if one of the optimization variables is PV inverter reactive power injection. Furthermore, the voltage optimization problem is mostly described as the objective of voltage deviation (VD) minimization, i.e., maintaining voltages within boundaries determined by grid codes. The general mathematical expression for VD is:

$$V_{dev} = \sum_{i \in N} (V_i - V^{nom})^2 \tag{5}$$

where:

V_{dev}—voltage deviation;
V_i—voltage at bus i;
V^{nom}—nominal voltage.

Another objective that appears is related to the voltage unbalance, commonly presented as the voltage unbalance factor (VUF). The definition of VUF is given in [52] as the ratio of negative $V^{-}_{sequence}$ and positive $V^{+}_{sequence}$ voltage sequences and is most often expressed in percentages:

$$VUF = \frac{V^{-}_{sequence}}{V^{+}_{sequence}}. \tag{6}$$

In addition to voltage optimization, the following objectives also appear: (i) power loss minimization [53–55], (ii) on load tap changer (OLTC) switching operation minimization [56], (iii) PV cost minimization [38], (iv) reactive power injection/absorption minimization [57], (v) active power curtailment (APC) minimization [58], (vi) cost of purchased energy minimization [59], (vii) peak shaving minimization [59], and (viii) security margin index (SMI) minimization [59]. The mathematical expressions of the commonly used objectives are given in Table 2.

Table 2. Mathematical expressions of the commonly used objectives in voltage optimization problems.

Objective	Formulation	Explanation
Power loss minimization [53–55]	$\sum_{k=i}^{N} g_{ik}(V_i^2+V_k^2-2V_iV_k\cos\theta_{ik})$ $\sum_{(i,k)\in B} r_{ik}l_{ik,t}$	V_i, V_k—voltage magnitude at i th and k th buses θ_{ik}—phase angle ith and kth elements of conductance g_{ik} $l_{ik,t}$ and r_{ik}—square value of current and resistance of branch line from bus i to bus k
OLTC tap operation minimization [56]	$\sum_{m=1}^{M} s_{m,t}$	M—number of discrete devices $s_{m,t}$—status of discrete device m at time t
APC minimization [58]	$\sum_{i=1}^{N} \lvert P_{t,i}^{PV,curt}\rvert$	$P_{t,i}^{PV,curt}$—curtailed active power of PV at time t
PV inverter loss minimization [38]	$\sum_{p=1}^{3}\sum_{i\in\gamma}(k_{i1}^{p}{S_{PVi}^{p}}^{2}+k_{i2}^{p}S_{PVi}^{p}+k_{i3}^{p})$	p—phases γ—set of buses with PVs S_{PVi}^{p}—apparent power k_{i1}^{p}, k_{i2}^{p}, k_{i3}^{p}—coefficients of each inverter's efficiency data
Reactive power inj./abs. minimization [57]	$\lvert Q_{inj.}\rvert/\lvert Q_{abs.}\rvert$	$Q_{inj.}$ and $Q_{abs.}$—injected/absorbed reactive power
Cost of energy minimization [59]	$\sum_{t\in T}\alpha_t P_{1,t}\Delta t$	α_t—price of energy at tth time $P_{1,t}$—active power imported from the external network at time t Δt—duration of time intervals
Security margin maximization [59]	$\sum_{t\in T}(1-min\lvert\frac{I_{l,t}-I_l^r}{I_l^r}\rvert)$	$I_{l,t}$—line current in lth line at time t I_l^r—ampacity of line current in lth line

In power systems, the conventional power flow is both nonlinear and nonconvex and commonly solved by the Newton–Raphson iterative method. In constrained OPF applications, equality constraints incorporate conventional power flow equations and other constraints to ensure balance. A detailed version of the power flow is named AC power flow [60]. AC power flow as a constraint in OPF is most often formulated in the polar form [60]:

$$P_i = \sum_{k=i}^{N} |V_i||V_k||Y_{ik}|\cos(\delta_i-\delta_k-\theta_{ik}) \tag{7}$$

$$Q_i = \sum_{k=i}^{N} |V_i||V_k||Y_{ik}|\sin(\delta_i-\delta_k-\theta_{ik}) \tag{8}$$

where:

P_i—active power at bus i;
Q_i—reactive power at bus i;
V_i—voltage magnitude at bus i;
V_k—voltage magnitude at bus k;
Y_{ik}—ikth element of bus admittance matrix $\mathbf{Y}_{bus}$;
δ_i—voltage phase angle at ith bus;
δ_k—voltage phase angle at kth bus;
θ_{ik}—phase angle of ikth element of bus admittance matrix $\mathbf{Y}_{bus}$.

Besides AC power flow, the authors use two other formulation approaches: decoupled AC power flow [49] and DC power flow [50]. In decoupled AC power flow, active and reactive powers are decoupled as a function of voltage angle and voltage magnitude, respectively. Assumptions made for the DC power flow formulation include purely imaginary elements of Y and a small difference between two voltage angles of two adjacent busses.

Various inequality constraints are given in [48,61]:

- control variables limit;
- limits for power generation (active and reactive power upper and lower limits);
- network operational limit determined in the network analysis (e.g., MVA limit).

Voltage optimization needs to meet the following constraint requirements:

1. Power flow equations given as Equations (7) and (8);
2. Voltage constraint
$$V_i^{min} \leq V_i \leq V_i^{max} \tag{9}$$
where V_i^{min} and V_i^{max} are the lower and upper voltage limits.
3. PV active and reactive power constraint
$$0 \leq P_{PV,i} \leq P_{PV,av,i} \tag{10}$$
$$-\sqrt{S_{PV,i}^2 - P_{PV,i}^2} \leq Q_{PV,i} \leq \sqrt{S_{PV,i}^2 - P_{PV,i}^2} \tag{11}$$
where $P_{PV,i}$, , Q_{PV_i}, and $S_{PV,i}$ are active, reactive, and apparent powers at bus i. $P_{PV,av,i}$ is available active power at bus i.
4. Line current (thermal) constraint
$$I_{ik}^{min} \leq I_{ik} \leq I_{ik}^{max} \tag{12}$$
where I_{ik}^{min} and I_{ik}^{max} are the lower and upper limits of the line current between buses i and k.
5. OLTC tap position constraint (if it is included)
$$T_i^{min} \leq T_i \leq T_i^{max} \tag{13}$$
where T_i^{min} and T_i^{max} are the lower and upper positions of OLTC tap at bus i.
6. Capacitor constraint (if it is included)
$$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max} \tag{14}$$
where Q_{Ci}^{min} and Q_{Ci}^{max} are the lower and upper limits of capacitor reactive power at bus i.
7. Energy storage constraint (if it is included)
$$SoC_{i,t}^{min} \leq SoC_{i,t} \leq SoCi, t^{max} \tag{15}$$
where $SoC_{i,t}^{min}$ and $SoC_{i,t}^{max}$ are the lower and upper limits of the charge state of the storage system at time t.

The voltage optimization problem can be single-objective or multi-objective. OPF objectives and variables used in the review papers are categorized and summarized in Table 3.

Table 3. Overview of objectives and variables.

Reference	Single/ Multi-Objective	Objectives	Variables
[62]	multi-objective	min VD from 0.95 pu threshold, min losses, min reactive power from capacitors	PV inverter reactive power, OLTC, SC, and
[63]	multi-objective	min losses, min VD—DN, min active power curtailed from available power—prosumer	PV active and reactive power
[64]	multi-objective	min VD from expected CVR voltage, min losses	PV inverter reactive power, OLTC/AVR, and CBs

Table 3. *Cont.*

Reference	Single/ Multi-Objective	Objectives	Variables
[65]	single-objective	min VD	PV inverter reactive power, OLTC
[38]	multi-objective	min losses, min VD, min VUF, min PV generation cost, min PV APC cost	PV inverter reactive power
[66]	multi-objective	min losses, min VD, improvement VSI	PV inverter reactive power and static compensator
[53,54,67–69]	multi-objective	min losses, min VD	PV inverter reactive power
[70]	multi-objective	min VD, min losses	PV inverter reactive power, CBs, and OLTC
[71]	single-objective	min VUF	PV inverter active and reactive power, power injected by TS
[72]	single-objective	min VD	PV inverter reactive power
[73]	multi-objective	min losses, min cost of APC and generated/consumed reactive power, min VD	PV inverter reactive power
[74]	multi-objective	min VD, min voltage unbalance	PV inverter reactive power, OLTC, VR, and CB
[75]	multi-objective	min losses, min VD, min VUF	PV inverter reactive power
[32]	single-objective	min VUF	PV inverter reactive power
[76]	single-objective	min VD	PV inverter reactive power, OLTC
[77]	multi-objective	min losses, min VD, min control action of OLTC and SC	PV inverter reactive power, OLTC, SC
[78]	single-objective	min VD	PV inverter reactive power, OLTC
[79]	multi-objective	min VD, min losses	PV inverter reactive power, OLTC, and SC
[57]	multi-objective	min VD, min losses, min reactive power injection, and absorption	PV inverter reactive power
[80]	multi-objective	min VD, min losses	PV inverter reactive power, OLTC
[81]	single-objective	min VD	PV inverter reactive power, OLTC, and VR
[58]	multi-objective	min VD, min losses, min APC	PV inverter reactive power, OLTC and CB
[55]	multi-objective	min VD, min losses	PV and EV inverter reactive power, the compensation device
[56]	multi-objective	min VD, min OLTC tap operation	PV inverter reactive power, OLTC
[82]	single-objective	min VD	PV inverter reactive power, charge/discharge rate of ESS
[83]	multi-objective	min losses, min VUF	PV inverter reactive power
[34]	multi-objective	min cost, min losses, min cost associated with active power setpoints, min VD	PV inverter active and reactive power
[84]	multi-objective	min active and reactive power output, min VD	PV inverter active and reactive power
[37]	multi-objective	min VD, min losses, min peak of reactive power	PV inverter reactive power
[85]	multi-objective	min VD, min losses	PV inverter reactive power, OLTC, CB
[59]	multi-objective	min VUF, min cost of purchased energy, min peak shaving, min losses, min SMI, min VD	PV inverter reactive power, EV active and reactive power, bus voltages at all time intervals of the day
[86]	multi-objective	min VUF, min losses	PV inverter reactive power, OLTC, CB
[87]	single-objective	min VD	PV inverter reactive power
[88]	multi-objective	min VD, min losses	PV inverter reactive power, SC, OLTC, ESS
[89]	multi-objective	min VD, min losses, min number of switching operations of OLTC and CB, min APC	PV inverter active and reactive power, CB, OLTC
[90]	multi-objective	min VD, min operational cost	PV inverter active and reactive power, CB, OLTC, ESS
[91]	multi-objective	min VD, min losses, min peak of reactive power	PV reactive power
[39]	single-objective	min VD	PV inverter reactive power

The abbreviations are as follows: CVR: conservation voltage reduction; VSI: voltage stability index; SC: shunt capacitor; AVR/VR: automatic voltage regulator; CB: capacitor bank.

According to the literature review, the multi-objective problem prevails.

Besides PV inverter reactive power, other variables include: (i) PV active power, (ii) OLTC, (iii) CB, (iv) static compensator, (v) reactive power from the substation, (vi) VRs, (vii) charge/discharge rate of ESS, (viii) EV active power, and (ix) SC.

3.2. Objectives and Variables—Discussion

Figure 7 represents objectives quantitatively. Almost all objectives include VD. In multi-objective problems, VD is most combined with losses, however, many other objectives also appear.

If OPF is regarded as a part of the distribution energy management system (DEMS), the dominance of the multi-objective formulation of OPFs is logical. DSO tries to reach the optimal operation point regarding several objectives and the most commonly used ones are loss minimization together with voltage deviation minimization. Additionally, active power curtailment (APC) minimization is frequently a combined objective with the minimization of voltage deviations. Other objectives are rare and they are used only in a few papers.

The variables are presented quantitatively in Figure 8.

A similar conclusion can be made regarding optimization variables. DSO tries to utilize all the available controls such as OLTC tap settings, CB reactive power, and ESS variables. Some of the variables are continuous but some are discrete (such as OLTC tap settings), which will affect the formulation of the OPF problem (the appearance of integer variables) and largely the choice of the solution method.

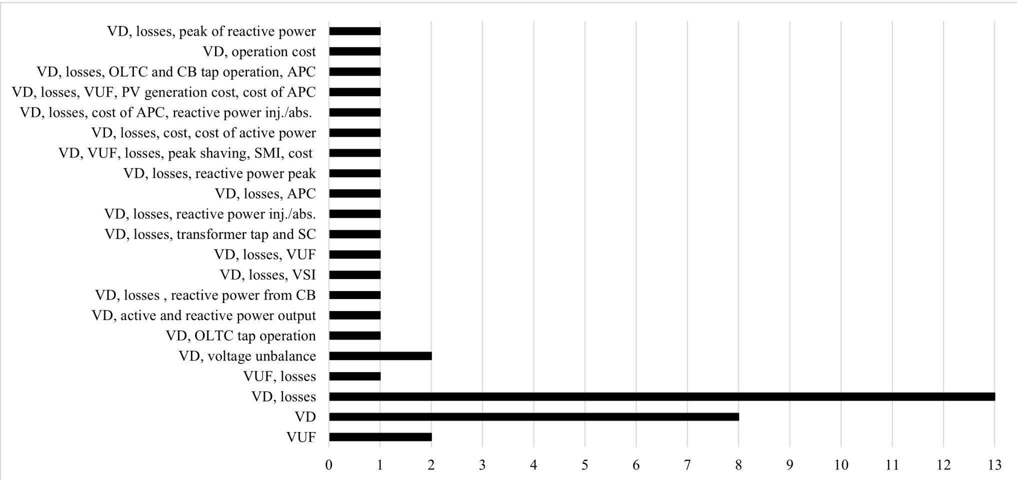


Figure 7. Quantitative presentation of the objectives.

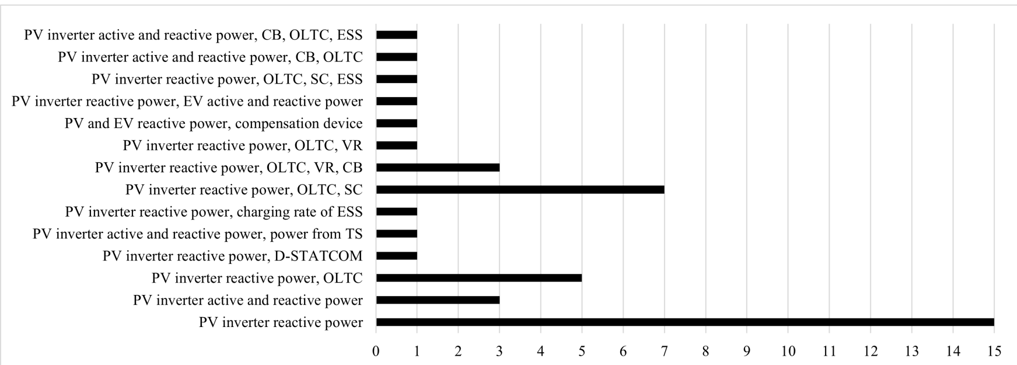


Figure 8. Quantitative presentation of the variables.

4. Voltage Optimization in PV-Rich Distribution Networks—Formulation and Solution Methods

The complexity of the OPF depends on the power flow formulation approach. If the original AC power flow equations are used for OPF formulation, an optimization problem is nonlinear and hard to solve. Thus, many researchers try to simplify OPF formulation in order to obtain a linear or quadratic optimization problem that is easier to solve. According to [60], the OPF formulation can be classified into:

- nonlinear programming (NLP);
- linear programming (LP);
- quadratic programming (QP);
- mixed-integer linear programming (MILP);
- mixed-integer nonlinear programming (MINLP).

In early papers, continuous NLP formulation is used. All discrete variables are approximated as continuous for simplicity. This formulation includes nonlinear objectives and constraints. The LP formulation uses the DC power flow approach, i.e., both the objectives and the constraints are linear. Due to its simplicity, robustness, speed, and well-developed solution methods, it is an attractive OPF formulation, especially for industry [51]. However, due to the modeling assumptions, LP is not adequate for problems such as minimizing power losses, and a global optimum cannot be guaranteed. QP is a special case of NLP with quadratic objective and linear constraints and represents an alternative to LP. The inclusion of discrete variables (transformer tap settings, shunt capacitor settings, etc.) in NLP results in MINLP being the most realistic and accurate formulation of OPF, but also the most complex and difficult to solve. However, there is a trade-off between the system description and the tractability of the problem. One way is to linearize and apply MILP. For more details, see [60,92].

The OPF formulation determines which solution method is used. Figure 9 presents the mathematical formulation and solution methods. For each solution method in Figure 9, a scientific paper in which it is applied is listed. The basic categorization of OPF solution methods is divided into analytical methods and computational intelligence methods. The most commonly used analytical methods for linear OPF are the well-developed simplex methods [93], sequential linear programming (SLP) [94], and interior point methods (IPMs) [95]. In the first period, analytical iterative methods were applied to the NLP OPF. They were Newton-based methods [96]; gradient methods—reduced gradient method (RG) [97], conjugate gradient method (CG) [98], and generalized reduced gradient method (GRG) [99]; IPMs [100]; sequential quadratic programming (SQP) [101]. Recently, computational intelligence methods have been applied to solving OPF problems. Computational intelligence methods have been developed to overcome the weak capabilities of analytical methods for solving global optimization [102]. Although computational intelligence methods do not require a precise mathematical formulation of the OPF problem, the authors include them in the group of solution methods that can solve nonlinear and integer formulations of the OPF since they can take into account nonlinearities in the original problem. Computational intelligence methods include artificial neural networks (ANNs) [103], genetic algorithms (GAs) [104], particle swarm optimization (PSO) [105,106], ant colony optimization (ACO) [107,108], bacterial foraging algorithm (BFA) [109], simulated annealing (SA) [110], tabu search (TS) [111], and fuzzy logic (FL) [112].

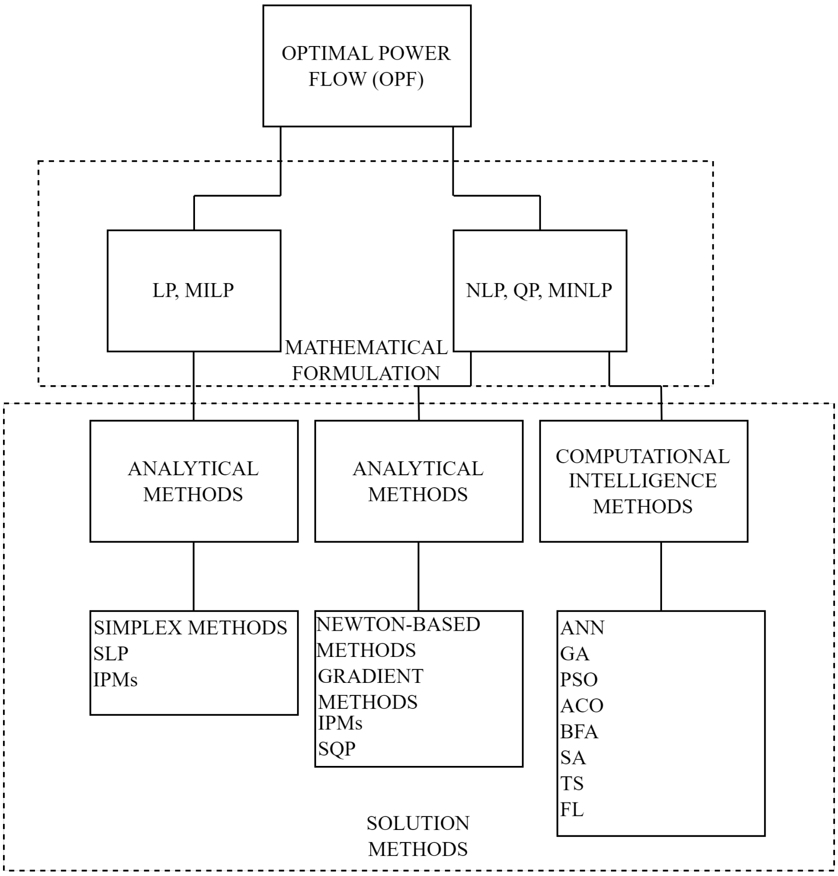


Figure 9. Mathematical formulation and solution methods used in OPF solving.

4.1. Analytical Methods

Classical analytical methods are used in multi-field optimization problems. In addition to the basic methods such as LP, QP [69], NLP, MINLP [76], and MILP, some papers deal with problems that reduce to the basic ones (see Table 4). In [65], SLP is developed to solve the optimization problem in real time. To obtain global optima, SQP has been developed in [38]. The iterative gradient projection method is implemented to specify VAR outputs for voltage optimization in [87] and additionally, active power outputs in [84]. A method for solving linear and nonlinear optimization problems was developed in [34,78]. The alternating direction method of multipliers (ADMM), which is one of the augmented Lagrangian-based methods, was developed as one of the most used methods for a network optimization problem. In ADMM, the optimization problem is decomposed into subproblems to deal with it. The subproblems are coordinated to seek the global optimal solution. The authors in [70,72,73] solve the voltage optimization problem using ADMM.

Table 4. Overview of formulation and analytical methods.

Formulation	Analytical Methods	Reference
NLP	ADMM-based method	[69]
	IPM	[36]
	SQP	[54]
LP	SLP	[63]
QP	QP	[52,53,74]
	Gradient projection methods	[59,82]
	ADMM-based method	[70,71]
MILP	MILP	[58]
MINLP	QP	[74]
	IPM	[76]

4.2. Computational Intelligence Methods

In recent years, computational intelligence methods have been increasingly used to solve voltage optimization problems. One of the main advantages of computational intelligence methods is that they do not require a mathematical formulation of the optimization problem. For the sake of unification and formality, the authors keep the formulation of the OPF problem in Table 5 even though it is not required for computational intelligence methods. The most commonly used methods are GA [37,57,62,83] and PSO [64,82,85,88]. Other computational intelligence methods that appear in the literature are the sine-cosine algorithm (SCA) [66], feasibility pump (FP) method [67], sparrow search algorithm (SSA) [74], pattern search algorithm [80], and grey wolf optimization (GWO) [81]. In some papers, hybrid methods are applied. In [79], a GA is applied to solve the day-ahead scheduling optimization problem in the first stage, while the pattern search algorithm (PSA) is used to solve the real-time optimization problem in the second stage. The branch-bound algorithm is combined with the IPM in [86] to solve the discrete problem. The combination of modified PSO and direct load flow (DLF) is used in [75]. DLF is used for power flow analysis and according to obtained data and PSO is used to evaluate network performance. In [77], the authors used both computational intelligence methods and analytical methods. In [55], five multi-objective evolution algorithms (MOEAs), named promising-region-based evolutionary many-objective algorithm (PREA), strength Pareto evolutionary algorithm 2 (SPEA 2), nondominated sorting genetic algorithm II (NSGA-II), nondominated sorting genetic algorithm III (NSGA-III), and two-phase framework (ToP), are used to determine the reactive power capacity of PVs and EVs. The results obtained by MOEAs are used to train a deep deconvolution neural network (DDNN) to solve the problem of voltage deviation and loss minimization. For inverter coordination, the authors in [113] use deep deterministic policy gradient (DDPG).

Table 5. Overview of formulation and computational intelligence methods.

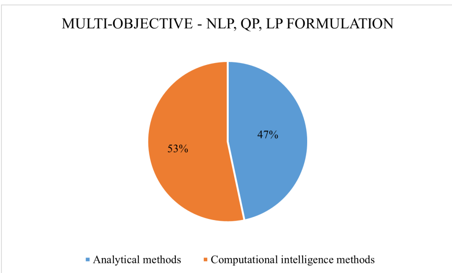
Formulation	Computational Intelligence Methods	Reference
NLP	GA	[37,57]
MINLP	GA	[62]
NLP	NDSGA II	[83]
NLP	PSO	[68,82]
MINLP	PSO	[64,85,88,114]
NLP	SCA	[66]
MINLP	C&CG algorithm	[53]
NLP	SSA	[74]
MINLP	GWO	[81]
MINLP	Modified PSO, DLF algorithm	[75]
MINLP	MOPSO, IPM	[77]
MINLP	GA,PSA	[79]
NLP	PREA, SPEA2, NSGA-II, NSGA-III, ToP, DDNN	[55]
MINLP	FP	[67]
MINLP	PSA	[80]
MINLP	NSGA-III	[89]
MINLP	ϵ-constrained method and FL	[90]
MINLP	DDPG	[113]
MINLP	ANN	[114]

4.3. Formulation and Solution Methods—Discussion

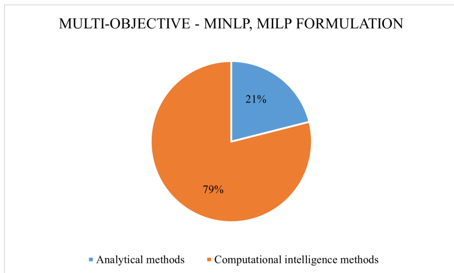
Analytical solution methods require a strictly mathematical formulation of the OPF problem, which can then be solved by an appropriate analytical method. Since there are a few effective analytical algorithms for solving nonlinear problems (especially with integer variables), most of the papers in which analytical methods are used transform the original NLP (or MINLP) into some of the more convenient forms—usually QP or MIQP. Transformations into a linear form (LP or MILP) are very rare due to the nature of the problem, i.e., the quadratic function of voltage deviation and poor performance of DC power flows in the environment of the DN (ratio R/X is not as small as in the TN).

According to Table 5, the popularity of computational intelligence methods can be observed. According to Figure 10, a decision about which solution method would be used depends on the objective and mathematical formulation. To briefly address Table 3, multi-objective optimization problems dominate. In single-objective problems, analytical solution methods prevail. Analytical methods require that a multi-objective (usually known as Pareto optimization) problem transforms (scalarizes) into a single-objective using weighting coefficients, which is not a straightforward procedure. Computational intelligence methods are most used for multi-objective problems. A comparison of analytical and computational intelligence methods is presented in Table 6.

Analytical methods are well-developed and applicable in systems where the requirements of modeling accuracy are low. Analytical methods are able to straightforwardly find an optimal solution but there is no guarantee that the optimum is global. If multiple local optima exist, global optima cannot be guaranteed and the analytical method can stuck in local optima. To apply the analytical method, it is necessary to perform a transformation of the original problem to a level that it can solve. This is where the problem of trade-off comes in. On the one hand, there is an accurate real-life system description and, on the other hand, there is an applicable solution method. Some shortcomings of analytical methods are solved by computational intelligence methods. These methods do not depend on mathematical formulation because they required only parameters that can be calculated separately (for example solution of the power flows). Compared to analytical methods, a hard computational effort is required and there is no guarantee of finding an optimal solution thus some expert knowledge of the system is needed. In recent years, computational intelligence methods are used in co-simulation with proven power flow tools DIgSILENT PowerFactory [41], DLF [75], OpenDSS [115], etc. This approach simplified the application of computational intelligence methods for large-scale DNs.



(**a**)



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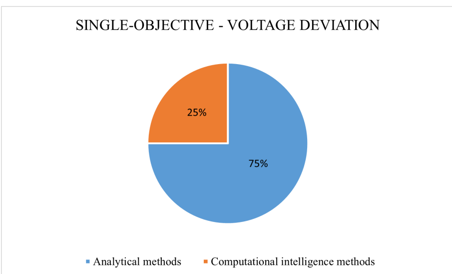

(**c**)

Figure 10. Solution methods for different objectives and formulations. (**a**) Multi-objective problem and continuous formulation. (**b**) Multi-objective problem including integer variables. (**c**) Single-objective problem.

Table 6. Comparison of analytical and computational intelligence methods.

	Advantages	Shortcomings
Analytical methods (simplex method, SLP, SQP, ADMM, gradient projection method, IPM)	- well-developed methods - fast computational performance of linear methods and IPMs	- stuck in local optima - modeling accuracy problem - the sensibility of initial conditions - cannot handle the multi-objective problem properly
Computational intelligence methods (evolutionary and biologically inspired methods, artificial intelligence methods, FL)	- do not depend on mathematical formulation - convergence is easier to set up compared to analytical methods	- hard computational effort - do not guarantee optima

4.4. Test Network Models

To validate the efficiency of different solution methods for the voltage optimization problem, the authors use test network models that can be divided into a standard test model and a test model based on real-life examples. The most common test network models used in literature represent IEEE test network models which, depending on the number of buses, can be IEEE–13 bus, IEEE–15 bus, IEEE–33 bus, IEEE–34 bus, IEEE–37 bus, IEEE–69 bus, IEEE–123 bus, and IEEE–8500 bus. Almost all have radial topology. According to the processed problem, some authors modify standard test models. For instance, the standard test model [70] is modified according to balance. Real-life-based models represent urban residential feeders located in the US, China, Italy, Egypt, Australia, Ireland, and the UK. Unbalanced networks are mostly low voltage and belong to real-life models. In Table 7, test network models, their voltage level, and balance are summarized. According to the reviewed literature, more authors utilize standard test network models IEEE–33 bus, IEEE–69 bus, and IEEE–123 bus node due to their flexibility and robustness. One possible problem that can appear is the OPF application for unbalanced DNs. For instance, the authors in [72] reduce an unbalanced system to a balanced assuming that voltage magnitudes between phases are analogous and phase angles on nodes are not drastic. Therefore, an unbalance between phases is low, and almost balanced. For more, see [72].

Table 7. Overview of test network models.

Reference	Test Network Model	Voltage Level	Balanced/Unbalanced
[32,79,80]	IEEE–34 bus	MV–24.9 kV and 4.16 kV	Balanced
[70]	IEEE–34 bus modified according to balance	MV–24.9 kV and 4.16 kV	Unbalanced
[55,63,67,81,82,85,89,90]	IEEE–33 bus	MV–12.66 kV	Balanced
[63]	Real–266 bus, Shenzen, China	MV–20 kV	Balanced
[53,64,83,88,113]	IEEE-123 bus	MV–4.16 kV	Unbalanced
[70,72]	IEEE–123 bus modified according to balance	MV–4.16 kV	Balanced
[65]	Real distribution feeder–187 bus	MV–12.47 kV and LV–120/240 V	Balanced
[38,75]	Perth Solar City–101 bus	LV–415/240 V	Unbalanced
[66]	Tala City, Egypt–37 bus	MV–11 kV	Balanced
[67,76,78,81]	IEEE–69 bus	MV–12.66 kV	Balanced
[32,57]	IEEE–13 bus	MV–4.16 kV	Balanced
[70]	IEEE–13 bus	MV–4.16 kV	Unbalanced

Table 7. *Cont.*

Reference	Test Network Model	Voltage Level	Balanced/Unbalanced
[71]	Real UK 1	LV–0.4 kV	Unbalanced
[72]	IEEE–15 bus	MV–11 kV	Unbalanced
[74]	IEEE–8500 bus	MV and LV	Both
[75]	Real Australian–565 bus	MV–22 kV and LV–415 V	Both
[68]	22 bus	MV–11.4 kV	Balanced
[78]	17 bus	MV–25 kV	Balanced
[56,113]	IEEE–37 bus	MV–4.16 kV	Unbalanced
[56]	Real Californian utility feeder–2884 bus	N/A	Unbalanced
[34]	Illustrative model	LV	N/A
[84]	K1 feeder–1747 bus in the southeastern US	MV and LV	N/A
[69,116]	33 bus	MV–12.66 kV	N/A
[69]	830 bus	N/A	N/A
[37,91]	Real South Korean–20 bus	MV–22.9 kV	Balanced
[59]	Real South Italian–16 bus	LV	Unbalanced
[39]	Real Irish suburban–85 bus	LV	N/A
[58]	Modified PG&E–69 bus	MV	Balanced
[114]	CIGRE–12 bus	MV	N/A
[116]	118 bus	MV	N/A

5. Conclusions

This paper aims to systematize and categorize scientific papers that are dealing with the optimization of voltage in the DN using the reactive power management of PV inverters. Additionally, the papers are categorized according to the optimization problem formulation and applied solution methods. It can be observed that the original voltage optimization problem is nonlinear due to a quadratic objective function and nonlinear power flow equations. Additionally, some authors propose a mixed-integer nonlinear formulation due to integer variables such as the OLTC tap setting. To solve such complex optimization problems, some authors use analytical methods and some use computational ones. In this review paper, the authors tried to point out the advantages and shortcomings of both approaches without favoring one. When analytical methods are used, the compromise regarding the transformation of the original problem into a standard one is present but the analytical approach enables the straightforward method to find the optimum of a well-defined optimization problem (although special attention is required in order to determine whether a calculated optimum is local or global). On the other hand, computational intelligence methods can solve complex optimization problems without the transformation of the original formulation but they required higher computational performance as well as more computational time. One of the trends in applying computational intelligence methods is using well-known power flow calculation tools in order to feed the computational intelligence method with multiple power flow solutions. This principle is recognized as co-simulation.

The research potential of the reviewed field lies in the fact that more and more inverter-based sources are installed in distribution networks worldwide. The importance of voltage optimization is specifically stressed in microgrids where voltage supports depend mainly on the inverter-based source. Since the PV active power production depends on variable and stochastic sun irradiation, further research direction in the field of voltage optimization will strive to create an adequate probabilistic formulation of the OPF problem which is computationally more demanding since large numbers of possible scenarios need to be analyzed. Some probabilistic OPF solutions are already created for the transmission system environment but their replication in the distribution network (or microgrid) is not straightforward. It is hard to foresee which solution methodology (analytical or computational intelligence) will show better performance in a probabilistic environment and there is still plenty of research challenges and gaps present for further research.

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