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Optimal Modeling of Load Variations in Distribution System Reconfiguration

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***Abstract*--Distribution networks have a prominent role in electricity delivery to individual consumers. Nevertheless, their energy losses are higher than transmission systems, which this issue affects the distribution operational costs. Hence, the minimization of power losses in distribution networks has particular importance for the system operators. Distribution network reconfiguration (DNR) is an effective way to reduce energy losses. However, some research works regarding DNR have not considered load variations in power loss calculations. Load level has an essential role in network losses determination and significantly influences the energy losses amount. On the other hand, considering load variations in DNR increases the computational burden and processing time of the relevant algorithms. Therefore, this paper presents an effective reconfiguration framework for minimization of distribution losses, while the energy demand is changing. The simulation results show the effectiveness of the proposed strategy for optimal reconfiguration of distribution systems in presence of load variations.**

***Keywords*—Distribution systems, DNR, energy losses, efficient reconfiguration strategy, demand variations.**

I. Introduction

Distribution systems are essential components of the power network [1] delivering the electrical energy of transmission systems [2]–[4] to electricity customers [5], [6] of the low-voltage side. However, part of the energy is lost during the delivery process due to the ohmic resistance of distribution lines. Active power losses [7] affect the operational costs and voltage profile of the distribution system. Hence, loss minimization is important to enhance the efficiency of distribution network and power quality [8].

One of the effective ways to reduce the losses is the distribution network reconfiguration (DNR). In DNR, system topology is changed by opening sectional switches (normally closed) and closing tie line ones (normally open) in a way that network radiality and connectivity has to be maintained [9].

Power losses minimization has been always important in distribution system reconfiguration [10]. Nonetheless, DNR beside loss reduction can include objectives such as power quality increment, network adequacy maximization [11]–[13], system stability enhancement, reliability improvement [14], [15], lines loading optimization [16], [17], reduction of line maintenance costs, supply capacity expansion, load balancing, increase in distributed generation (DG) [18] hosting, service restoration [19], quick fault isolation, and implementation of preventive maintenance plans.

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After publication of Merlin and Back's paper in 1975, much research has been done on the field of DNR with the aim of active power loss minimization. Some of these research works have employed different power flow methods for solving the problem such as DC, AC, Newton, optimal power flow (OPF), radial, simplified, and linearized load flow techniques. Some of them have proposed new strategies for the problem formulation such as loss change estimation, network partitioning and division, and Benders decomposition. Also, some others have presented various models for DNR based on linear, non-linear, integer, discrete, and binary programming techniques.

However, DC, radial, simplified and linearized power flows cannot accurately calculate network losses because of linearizations, simplifications, and approximations used in them. Also, linear sensitivity analysis employed in OPF and approximation of network losses in Newton method, as well as time-consuming AC power flow computations have decreased the efficiency of these methods in reconfiguration applications. Moreover, calculation of voltage drops at only extremes of tie lines in loss change estimation method and limited implementation of network partitioning and division approaches to only small distribution systems, plus a decrease in efficiency of Benders decomposition method by increasing non-linearity of the problem, reduce the effectiveness of such reconfiguration strategies. Furthermore, a piecewise linear approximation of power losses in linear programming and hard implementation of the model presented by integer programming, as well as higher mathematical efforts for the representation of the non-linear power flow equations as quadratic terms in non-linear programming degrade the performance of the proposed linear, integer, and non-linear programming models. Also, a step-by-step mechanism of peak load increment to find configurations with the smallest effect on losses increase has raised the computational time of discrete programming models. Despite the higher efficiency of the binary programming model compared to other programming approaches, load variations have not been considered in the above-mentioned models and strategies.

Although reconfiguration of distribution systems according to their peak loads rather than actual load levels provides the optimal configurations (the best switching proposals) for distribution networks, the calculated losses are inaccurate because distribution systems are not frequently operated under peak conditions. In this way, the maximum amount of minimum losses is computed instead of real optimal losses. Minimization of peak power losses is a quick way to find appropriate switching combinations, but in many reconfiguration applications, the real amount of power losses is required.

The calculation of network losses in a correct way is important when the losses cost is going to be optimized beside other objectives such as switching cost, maintenance and repair expenses, DG investment, capacitor installation budget, etc. For this issue, some papers have solved the DNR problem under load variations.

In [20], a traditional DNR problem was modeled considering a variable load pattern. In this approach, the load curve was divided into four levels and the load level of each bus was estimated by an artificial neural network (ANN). However, the performance of the proposed algorithm is degraded by selecting an inappropriate training set for ANN. In order to resolve this problem, a clustering technique was employed to determine the best training set in [21]. Although this procedure could enhance the performance of ANN, clustering the loads based on their values without considering their locations can decrease the precision of the solution method.

Also, in [22], distribution losses cost and capacitor investment were minimized by simultaneous network reconfiguration and optimal allocation of shunt capacitors considering the daily load curve. In order to decrease the processing time of the proposed heuristic algorithm, actual demand was approximated by four load levels. However, information about computation time has not been reported in the literature to see the results of load levels reduction in comparison with other reconfiguration approaches. Whereas, this approximation has significantly decreased the precision of losses cost calculations. This fact can affect the optimal place and number of capacitor banks (capacitor investment) and therefore changes the proposed switching scenarios.

Moreover, in [23], the power losses and switching costs were minimized through network reconfiguration in presence of DG considering seasonal power demand. Although the simulation results demonstrate a significant decrease in energy losses due to DG usage, the optimal solutions are not true because of ignoring DG investment and operational costs in the problem formulation. In [24], energy losses cost was minimized considering the daily load curve using an artificial immune system (AIS). Although including hourly power demand in DNR increases the modeling precision, computational burden and processing time are increased significantly. Moreover, the radial power flow used for branch current calculations has reduced the accuracy of the AIS algorithm.

In [25], hourly, weekly and seasonal load profiles were considered to maximize the annual investment return via network reconfiguration. The investment return contains cost saving due to loss reduction, the installation cost of communication equipment, and the maintenance cost of remote control switches. The results confirmed that the large amount of investment can be saved through the reconfiguration of distribution systems by automatic switches. However, as mentioned earlier, considering entire load levels in DNR causes a high computational burden for reconfiguration models. In order to minimize accurate power losses and propose a fast reconfiguration strategy, this paper developed an efficient model for distribution system reconfiguration considering load variations.

In the proposed model, the behavior of demand variations was formulated using hourly load levels by an equivalent load factor in a mixed-integer non-linear programming (MINLP) framework. The proposed model was applied to five test systems to show the effectiveness and robustness of the proposed approach for real DNR applications.

II. Load Variations Modeling

Generally, the power demand ($P(t)$) of a distribution system during operation period T with n load levels can be illustrated as the profile of Fig. 1.

In static reconfiguration, distribution system topology is determined according to peak load ($P(t_p)$) in the beginning of the operation period (t_0) and is considered to be a fix for whole operation time, because considering whole load profile values increases the computational burden and processing time significantly. On the other hand, the power losses cannot be calculated correctly if just peak load value is considered. This is an important challenge for distribution system operators because considering load profile in DNR calculations increases computational time and ignoring it decreases computational accuracy.

As mentioned earlier, correctly calculation of losses is very important when the DNR problem is optimized in order to achieve other goals besides power losses minimization. Accordingly, in current work, the load variations are modeled in efficient ways to reduce and increase the computational burden and precision of DNR problem, respectively.

A. Load Profile Model

In reconfiguration applications, specific load levels are usually available. Consequently, the load curve of Fig. 1 can be estimated by pricewise linear functions as (1).

$$P(t) = P_n + \frac{P_n - P_{n-1}}{t_n - t_{n-1}}\left(t - t_n\right) \quad t_{n-1} \le t \le t_n \;\; \forall n = 1,\ldots,T \qquad (1)$$

The precision of formulation (1) is increased by choosing smaller intervals for t (more load levels). These linear functions are shown in Fig. 2. Including all of these load levels in DNR increases the computational time of reconfiguration algorithms. Therefore, the average value of (1) (P_A) can be calculated by (2).

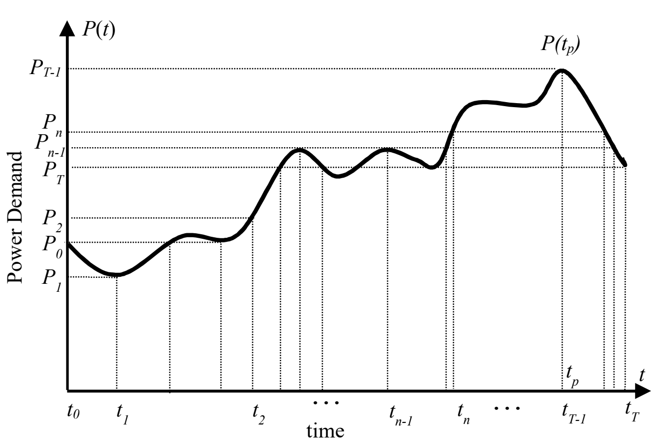

Fig. 1. Load profile.

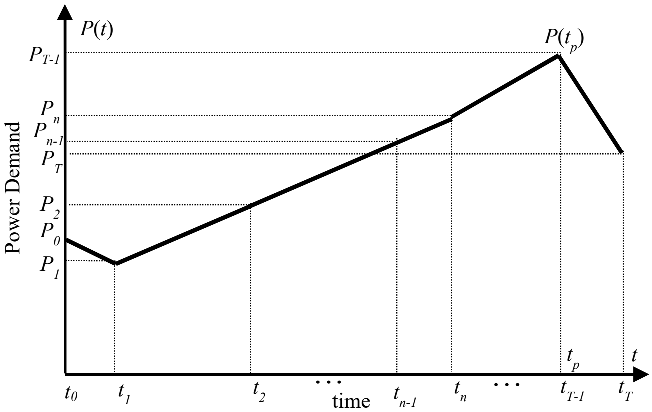

Fig. 2. Linearized load profile.

$$\begin{aligned} P_A &= \frac{1}{t_T - t_0}\int_{t_0}^{t_T} P(t)\,dt \\ &= \frac{1}{t_T - t_0}\sum_{n=1}^{t_T}\int_{t_{n-1}}^{t_n}\left(P_n + \frac{P_n - P_{n-1}}{t_n - t_{n-1}}\left(t - t_n\right)\right)dt \qquad (2) \\ &= \frac{1}{t_T - t_0}\sum_{n=1}^{t_T}\frac{P_n + P_{n-1}}{2}\left(t_n - t_{n-1}\right) \end{aligned}$$

Load levels are represented in terms of system peak load. Assuming each load level (P_n) is described as a percentage (L_n) of the peak load, (2) can be written as follows.

$$P_A = \frac{P(t_p)}{t_T - t_0}\sum_{n=1}^{t_T}\frac{L_n + L_{n-1}}{2}\left(t_n - t_{n-1}\right) \qquad (3)$$

In order to more efficiently and realistically reconfiguring distribution systems without any additional computational burden due to considering load variations, the peak load of each operation period should be included in DNR constraints and equivalent load factor (K_{eq}) should be embedded in the objective function.

$$K_{eq} = \frac{P_A}{P(t_p)} = \frac{1}{t_T - t_0}\sum_{n=1}^{t_T}\frac{L_n + L_{n-1}}{2}\left(t_n - t_{n-1}\right) \qquad (4)$$

B. Load Duration Curve (LDC) Model

In some reconfiguration applications, the load duration curve (LDC) is given rather than the load profile. The LDC of the profile shown in Fig. 1 can be obtained as Fig. 3 by arranging load levels from the peak to the lowest level. In this curve, Δt_n is the duration of load level P_n.

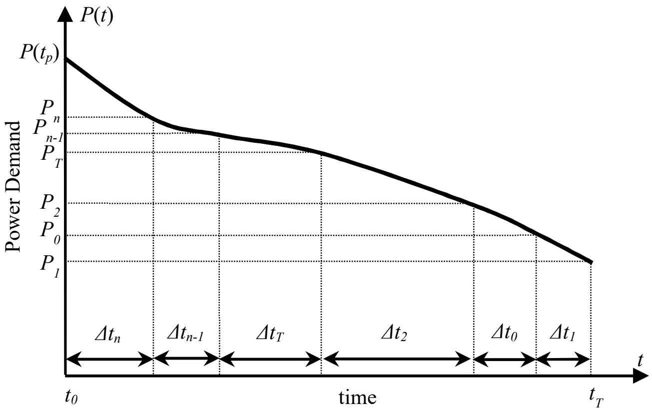

Fig. 3. Load duration curve.

Normalized LDC can be obtained as Fig. 4 by considering t_0=0, while vertical and horizontal axes are divided by peak load amount and t_T value, respectively. In this figure, Δt_n is represented as a percentage of whole load duration t_T ($\Delta t_n = N_n t_T$). The normalized LDC can be approximated by piecewise linear functions as Fig. 5.

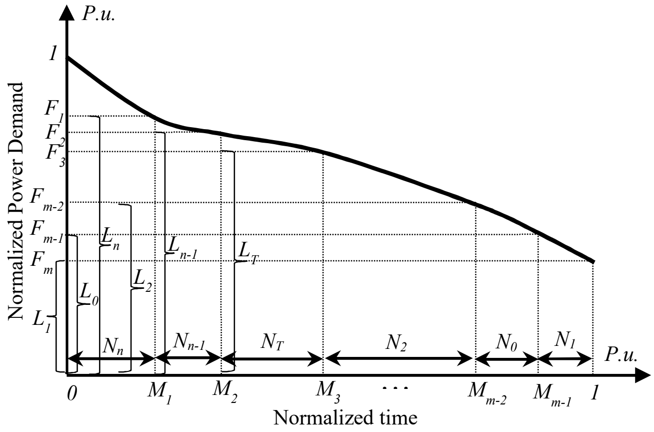

Fig. 4. Normalized load duration curve.

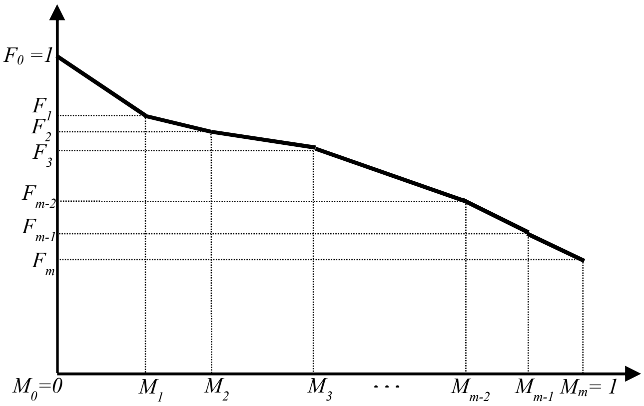

Fig. 5. Linear normalized LDC.

The equivalent load factor can be calculated as (5). The value of this factor will be between 0 and 1 that simulates load changes in terms of system peak load.

$$K_{eq} = \int_0^1 P(t)\,dt = \frac{1}{2}\sum_{m=1}^{n-1}\left(M_m - M_{m-1}\right)\left(F_m + F_{m-1}\right) \qquad (5)$$

Comparing (5) with (4) proves that K_{eq} has been calculated correctly because both equations give the same results.

C. Step Load Model

Sometimes, the peak load of each time interval (Pe_n) is considered instead of its real load variations. In this case, the power demand is assumed to be constant in each interval and the load profile of Fig. 1 is represented by step functions as Fig. 6. The equivalent load factor for the estimated load profile of Fig. 6 is calculated by (6) regarding the real operation period of load profile ($t_T - t_0$) in Fig. 1 and integral of Fig. 6 in a repetition interval of step load profile (from t_0 to t_{T+1}). In (6), peak load factor Le_{n-1} is the portion of peak load level $n-1$ (maximum power demand between t_2 and t_{n-1} in real load profile) of maximum demand ($Pe_{n-1} = Le_{n-1}P(t_p)$).

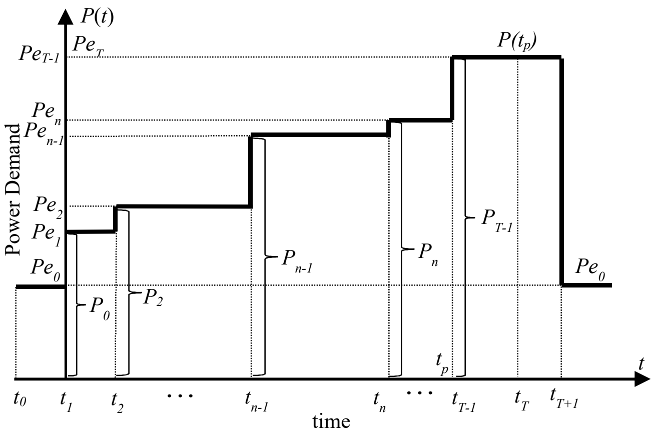

Fig. 6. Step load profile.

$$K_{eq}=\frac{P_A}{P(t_p)}=\frac{\frac{1}{t_T-t_0}\int_{t_0}^{t_{T+1}}P(t)dt}{P(t_p)}=\frac{\sum_{n=1}^{T+1}Pe_{n-1}\left(t_n-t_{n-1}\right)}{\left(t_T-t_0\right)P(t_p)} \tag{6}$$
$$=\frac{1}{\left(t_T-t_0\right)}\sum_{n=1}^{T+1}Le_{n-1}\left(t_n-t_{n-1}\right)$$

Equation (6) is helpful for including the effect of power demand variations in DNR problem when the peak load of each time interval is given as discrete numbers.

III. DNR Modeling Considering Load Variations

The DNR problem with the aim of energy losses (E_{Loss}) minimization considering the load profile of Fig. 1 can be formulated by (7) to (15).

$$Min\ C_T=\int_{t=t_0}^{t_T}C_l\sum_{ij\in\Omega^l}R_{ij}\left|I_{ij}(t)\right|^2+\sum_{i\in\Omega^b}\sum_{i\in\Omega^g}C_g n_i^g P_g^{\max} \tag{7}$$

subject to:

$$P_i^S(t)+\sum_{ki\in\Omega^l}P_{ki}(t)-\sum_{ij\in\Omega^l}P_{ij}(t)-\sum_{ij\in\Omega^l}R_{ij}\left|I_{ij}(t)\right|^2=P_i^D(t) \tag{8}$$

$$Q_i^S(t)+\sum_{ki\in\Omega^l}Q_{ki}(t)-\sum_{ij\in\Omega^l}Q_{ij}(t)-\sum_{ij\in\Omega^l}X_{ij}\left|I_{ij}(t)\right|^2=Q_i^D(t) \tag{9}$$

$$\left|V_i(t)\right|^2-\left|V_j(t)\right|^2=2\left[R_{ij}P_{ij}(t)+X_{ij}Q_{ij}(t)\right]+\left(R_{ij}{}^2+X_{ij}{}^2\right)\left|I_{ij}(t)\right|^2+b_{ij}(t)\qquad\forall i,j\in\Omega^b \tag{10}$$

$$\left|V_j(t)\right|^2\left|I_{ij}(t)\right|^2=P_{ij}{}^2(t)+Q_{ij}{}^2(t)\qquad\forall j\in\Omega^b,\,ij\in\Omega^l \tag{11}$$

$$\sum_{ij\in\Omega^l}y_{ij}=\left|\Omega^b\right|-1 \tag{12}$$

$$V_{\min}^2\le\left|V_i(t)\right|^2\le V_{\max}^2\qquad\forall i\in\Omega^b \tag{13}$$

$$0\le\left|I_{ij}(t)\right|^2\le\left(I_{ij}^{\max}\right)^2y_{ij}\qquad\forall ij\in\Omega^l \tag{14}$$

$$\left|b_{ij}(t)\right|\le\left(V_{\max}^2-V_{\min}^2\right)\left(1-y_{ij}\right)\quad\forall ij\in\Omega^l \tag{15}$$

Where, Ω^l and Ω^b are set of distribution lines and buses, respectively. $P_{ij}(t)$ and $Q_{ij}(t)$ are active and reactive power flows of line ij in time t, respectively. R_{ij} is resistance and X_{ij} is the reactance of line ij. $P_i^S(t)$, $Q_i^S(t)$, $P_i^D(t)$, and $Q_i^D(t)$ are active and reactive powers of substation and demand on bus i in time t, respectively. $\left|I_{ij}(t)\right|$ and I_{ij}^{max} are the current flow magnitudes of line ij in time t and its maximum value. $\left|V_i(t)\right|$, V_{max}, and V_{min} are the voltage magnitude of bus i in time t and its maximum and minimum amounts, respectively. $b_{ij}(t)$ is a variable for representing the Kirchhoff's voltage law (KVL) in the loop formed by line ij at each time. y_{ij} is a binary variable for the switch status of line ij (0 for open and 1 for closed switches).

Equations (8) and (9) express nodal active and reactive power balances in time t (Kirchhoff's current law, KCL). Equation (10) describes the net summation of voltage drops of all lines in a planar loop, which has to be equal to zero every time (KVL). In this equation, $b_{ij}(t)$ will be zero, when the switch of line ij is closed at time t (KVL must be established) and will be a real number for open switches (KVL is not necessary). Also, (11) shows the relationship between line power flow and its active and reactive components. Equation (12) indicates the radiality constraint. Accordingly, the total number of lines under operation (total number of closed switches) has to be equal to the total number of buses minus one (according to graph theory). Constraints (13) and (14) represent voltage and current limits, respectively. (15) makes sure that the value of $b_{ij}(t)$ will be zero, if the switch of line ij is closed (y_{ij}=1) and a real number between V^2_{max}–V^2_{min} and V^2_{min}–V^2_{max} when the corresponding line is disconnected (y_{ij}=0). In order to convert the above-mentioned non-linear programming model to a convex mixed-integer non-linear optimization problem that can be solved by linear commercial solvers in classic optimization tools, (7)–(15) are modified as follows.

$$Min\ E_{Loss}=\sum_{n=0}^{T}\sum_{ij\in\Omega^l}R_{ij}I_{ij}^{sqr}(t_n) \tag{16}$$

subject to (12) and:

$$P_i^S(t_n)+\sum_{ki\in\Omega^l}P_{ki}(t_n)-\sum_{ij\in\Omega^l}P_{ij}(t_n)-\sum_{ij\in\Omega^l}R_{ij}I_{ij}^{sqr}(t_n)=P_i^D(t_n)\qquad\forall n=0,...,T \tag{17}$$

$$Q_i^S(t_n)+\sum_{ki\in\Omega^l}Q_{ki}(t_n)-\sum_{ij\in\Omega^l}Q_{ij}(t_n)-\sum_{ij\in\Omega^l}X_{ij}I_{ij}^{sqr}(t_n)=Q_i^D(t_n)\qquad\forall n=0,...,T \tag{18}$$

$$V_i^{sqr}(t_n)-V_j^{sqr}(t_n)=2\left[R_{ij}P_{ij}(t_n)+X_{ij}Q_{ij}(t_n)\right]+b_{ij}(t_n)+\left(R_{ij}{}^2+X_{ij}{}^2\right)I_{ij}^{sqr}(t_n)\quad\forall i,j\in\Omega^b,\,ij\in\Omega^l,\,n=0,...,T \tag{19}$$

$$V_j^{sqr}(t_n)I_{ij}^{sqr}(t_n)\ge P_{ij}{}^2(t_n)+Q_{ij}{}^2(t_n)\quad\forall ij\in\Omega^l,\,n=0,...,T \tag{20}$$

$$V_{\min}^2\le V_i^{sqr}(t_n)\le V_{\max}^2\qquad\forall i\in\Omega^b,\,n=0,...,T \tag{21}$$

$$0\le I_{ij}^{sqr}(t_n)\le\left(I_{ij}^{\max}\right)^2y_{ij}\quad\forall ij\in\Omega^l,\,n=0,...,T \tag{22}$$

$$\left|b_{ij}(t_n)\right|\le\left(V_{\max}^2-V_{\min}^2\right)\left(1-y_{ij}\right)\quad\forall ij\in\Omega^l,\,\forall n=0,...,T \tag{23}$$

Where, n is the number of load levels that is an integer number and $I_{ij}^{sqr}(t_n)$ and $V_i^{sqr}(t_n)$ are square of branch current and bus voltage magnitudes, respectively. Solving the convex mixed-integer non-linear programming (convex MINLP) model described by (16)–(23) and (12) is relatively time-consuming and needs higher computational efforts than conventional DNR (loss minimization without considering load levels). In order to resolve this problem, the following convex MINLP formulation is proposed.

$$Min\ E_{Loss} = T\sum_{ij\in\Omega^l}\left(K_{eq}\right)^2 R_{ij} I_{ij}^{sqr}(t_p) \quad (24)$$

subject to (12) and:

$$P_i^S(t_p) + \sum_{ki\in\Omega^l} P_{ki}(t_p) - \sum_{ij\in\Omega^l} P_{ij}(t_p) - \sum_{ij\in\Omega^l} R_{ij} I_{ij}^{sqr}(t_p) = P_i^D(t_p) \quad \forall n = 0,\ldots,T \quad (25)$$

$$Q_i^S(t_p) + \sum_{ki\in\Omega^l} Q_{ki}(t_p) - \sum_{ij\in\Omega^l} Q_{ij}(t_p) - \sum_{ij\in\Omega^l} X_{ij} I_{ij}^{sqr}(t_p) = Q_i^D(t_p) \quad \forall n = 0,\ldots,T \quad (26)$$

$$V_i^{sqr}(t_p) - V_j^{sqr}(t_p) = 2\left[R_{ij} P_{ij}(t_p) + X_{ij} Q_{ij}(t_p)\right] + b_{ij}(t_p) + \left(R_{ij}^2 + X_{ij}^2\right) I_{ij}^{sqr}(t_p) \quad \forall i,j\in\Omega^b,\ ij\in\Omega^l \quad (27)$$

$$V_j^{sqr}(t_p) I_{ij}^{sqr}(t_p) \ge P_{ij}^2(t_p) + Q_{ij}^2(t_p) \quad \forall j\in\Omega^b,\ ij\in\Omega^l \quad (28)$$

$$V_{\min}^2 \le V_i^{sqr}(t_p) \le V_{\max}^2 \quad \forall i\in\Omega^b \quad (29)$$

$$0 \le I_{ij}^{sqr}(t_p) \le \left(I_{ij}^{\max}\right)^2 y_{ij} \quad \forall ij\in\Omega^l \quad (30)$$

$$\left|b_{ij}(t_p)\right| \le \left(V_{\max}^2 - V_{\min}^2\right)\left(1 - y_{ij}\right) \quad \forall ij\in\Omega^l \quad (31)$$

IV. Numerical Results

In order to show the efficiency of the proposed reconfiguration approach, the model described by (24)–(31) and (12), as well as the convex MINLP model were tested on a few distribution systems in an operation period of 24 h (T=24) using CPLEX in AMPL. Table I presents the peak load factors (Le_n) of the final consumer at each bus over the operation period.

The peak load of a bus should be multiplied by the peak load factor of each hour to obtain hourly peak load levels of the corresponding bus. The equivalent load factor should be calculated by (6) according to the load data of Table I. The results of the proposed idea, such as open switches (disconnected lines), daily energy losses (kWh), and computing time (s) are listed in Tables II to VI for different test systems. It can be seen that the proposed model, when the equivalent load factor is embedded in the DNR formulation, is much accurate than DNR without considering load variations.

TABLE I
Peak Load Factors of Consumers

Hour	load factor	Hour	load factor	Hour	load factor
1	0.35	9	0.62	17	0.68
2	0.29	10	0.57	18	0.92
3	0.28	11	0.52	19	1
4	0.27	12	0.51	20	0.93
5	0.27	13	0.54	21	0.86
6	0.30	14	0.52	22	0.79
7	0.42	15	0.51	23	0.69
8	0.60	16	0.55	24	0.49

TABLE II
Numerical Results for 7-Bus Distribution System [19]

Items	Open Switches	Energy Losses	Time
DNR disregarding load variations	5	19.62	0.28
DNR considering hourly load levels	5	7.09	2.19
DNR with equivalent load factor	5	6.75	0.28

TABLE III
Numerical Results for 16-Bus Distribution System [19]

Items	Open Switches	Energy Losses	Time
DNR disregarding load variations	17,19,26	11187	0.63
DNR considering hourly load levels	17,19,26	3990	7.18
DNR with equivalent load factor	17,19,26	3843	0.63

TABLE IV
Numerical Results for 28-Bus Distribution System [19]

Items	Open Switches	Energy Losses	Time
DNR disregarding load variations	11,20,21,28	952.7	1.19
DNR considering hourly load levels	11,20,21,28	331.04	40.8
DNR with equivalent load factor	11,20,21,28	327.25	1.19

TABLE V
Numerical Results for 33-Bus Distribution System [19]

Items	Open Switches	Energy Losses	Time
DNR disregarding load variations	7,9,14,32,37	3349	4.19
DNR considering hourly load levels	7,9,14,32,37	1178	1296.4
DNR with equivalent load factor	7,9,14,32,37	1150	4.19

TABLE VI
Numerical Results for 49-Bus Distribution System [19]

Items	Open Switches	Energy Losses	Time
DNR disregarding load variations	34,39,45,49,51	173.44	2.52
DNR considering hourly load levels	34,39,45,49,51	62.63	186.48
DNR with equivalent load factor	34,39,45,49,51	59.58	2.52

In this case, nearly real energy losses are calculated instead of maximum losses obtained in DNR disregarding load levels. Also, it is observed that the proposed formulation has resulted in energy losses amount very close to real energy losses when whole load levels are considered in DNR model. However, the proposed approach can solve the problem much faster than DNR considering hourly load levels. The proposed model is very efficient for solving hard combinatorial large-scale static DNR problems considering load variations because it is as fast as the conventional DNR model without load variations and is almost as accurate as reconfiguration models considering whole load variations.

V. Conclusion

In distribution systems, the load is variable during the operation period and is changed according to the power demand of electricity consumers from peak value to the base power. Load variations have an important role in energy losses calculations and affect combinatorial distribution system reconfiguration, in which the DNR problem is optimized beside other operation costs. Considering load variations in distribution system reconfiguration increases both computational burden and model precision. Thus, in this paper, an efficient approach was presented to solve the DNR problem in presence of load variations without any additional computation time. The results show high accuracy of the model compared to when the DNR is solved without load variations and low computational time compared to when all load levels are considered in DNR. The proposed reconfiguration strategy causes accurate solutions are obtained in a short processing time.

VI. References

[1] H. Shayeghi, H. Hosseini, A. Shabani, and M. Mahdavi, “GEP considering purchase prices, profits of IPPs and reliability criteria using hybrid GA and PSO,” *Int. J. Electr. Comput. Eng.*, vol. 2, no. 8, pp. 1619–1625, 2008.

[2] M. Mahdavi, C. Sabillón, M. Ajalli, H. Monsef, and R. Romero, “A real test system for power system planning, operation, and reliability,” *J. Control Autom. Electr. Syst.*, vol. 29, no. 2, pp. 192–208, 2018.

[3] M. Mahdavi and E. Mahdavi, “Evaluating the effect of load growth on annual network losses in TNEP considering bundle lines using DCGA,” *Int. J. Tech. Phys. Probl. Eng.*, vol. 3, no. 4, pp. 1–9, 2011.

[4] M. Mahdavi and H. Monsef “Review of static transmission expansion planning,” *J. Electr. Control Eng.*, vol. 1, no. 1, pp. 11–18, 2011.

[5] M. Khodayari, M. Mahdavi, and H. Monsef, “Simultaneous scheduling of energy & spinning reserve considering customer and supplier choice on reliability,” in *Proc. 19th Iranian Conf. Electr. Eng.*, Tehran, Iran, 2011, pp. 491–496.

[6] M. Khodayari, H. Monsef, and M. Mahdavi, “Customer reliability based energy & SR scheduling at hierarchical level II,” in *Proc. 27th Int. Power Syst. Conf.*, Tehran, Iran, 2012, pp. 1–11, 2012.

[7] S. Jalilzadeh, A. Kazemi, M. Mahdavi, and H. Haddadian, “TNEP considering voltage level, network losses and number of bundle lines using GA,” in *Proc. Third Int. Conf. Electr. Utility Deregulat. Restruct. Power Technol.*, Nanjing, China, pp. 1580–1585, 2008.

[8] M. Mahdavi, L. H. Macedo, and R. Romero, “A mathematical formulation for distribution network reconfiguration,” in *Proc. 7th Regional Conf. Electricity Distrib.*, Tehran, Iran, 2019, pp. 1–5.

[9] M. Mahdavi and R. Romero, “Reconfiguration of radial distribution systems: An efficient mathematical model,” *IEEE Latin Am. Trans.*, vol. 19, no. 7, pp. 1172–1181, 2021.

[10] L. H. Macedo, J. F. Franco, M. Mahdavi, and R. Romero “A contribution to the optimization of the reconfiguration problem in radial distribution systems,” *J. Control, Autom. Electr. Syst.*, vol. 29, no. 6, pp. 756–768, 2018.

[11] H. Shayeghi, M. Mahdavi, and H. Haddadian, “DCGA based-transmission network expansion planning considering network adequacy,” *Int. J. Electr. Comput. Eng.*, vol. 2, pp. 2875–2880, 2008.

[12] H. Shayeghi and M. Mahdavi, “Optimization of transmission lines loading in TNEP using decimal codification based GA,” *Int. J. Electr. Comput. Eng.*, vol. 2, no. 5, pp. 942–947, 2008.

[13] H. Shayeghi, M. Mahdavi, and A. Kazemi, “Discrete particle swarm optimization algorithm used for TNEP considering network adequacy restriction,” *Int. J. Electr. Comput. Eng*, vol. 3, no. 3, pp. 521-528, 2009.

[14] H. Hosseini, S. Jalilzadeh, V. Nabaei, G. R. Z. Govar, and M. Mahdavi, “Enhancing deregulated distribution network reliability for minimizing penalty cost based on reconfiguration using BPSO,” in *Proc. 2nd IEEE Int. Conf. Power and Energy*, Johor Bahru, Malaysia, 2008, pp. 983–987.

[15] A. Kimiyaghalam, M. Mahdavi, A. Ashouri, and M. Bagherivand, “Optimal placement of PMUs for reliable observability of network under probabilistic events using BABC algorithm,” in *Proc. 22nd Int. Conf. Exhib. Electricity Distrib.*, Stockholm, Sweden, 2013, pp. 1–4.

[16] M. Mahdavi, H. Monsef, and A. Bagheri, “Transmission lines loading enhancement using ADPSO approach,” *Int. J. Electr. Computer Eng.*, vol. 4, no. 3, pp. 556–561, 2010.

[17] H. Shayeghi, H. A. Shayanfar, M. Mahdavi, and A. Bagheri, “Application of binary particle swarm optimization for transmission expansion planning considering lines loadinga,” in *The 2009 Int. Conf. Artificial Intell.*, Las Vegas, Nevada, USA, pp. 653–659, 2009.

[18] M. Mahdavi, H. Monsef, A. Bagheri, and A. Kimiyaghalam, “Dynamic transmission network expansion planning considering network losses, DG sources and operational costs-part 1: review and problem formulation,” *WULFENIA J.*, vol. 19, no. 10, pp. 242–257, 2012.

[19] M. Mahdavi, “New models and optimization techniques applied to the problem of optimal reconfiguration of radial distribution systems,” FAPESP, SP, Brazil, Rep. no. 2016/12190-7, 2019.

[20] H. Kim, Y. Ko, and K. H. Jung, “Artificial neural-network based feeder reconfiguration for loss reduction in distribution systems,” *IEEE Trans. Power Del.*, vol. 8, no. 3, 1993.

[21] H. Salazar, R. Gallego, and R. Romero, “Artificial neural networks and clustering techniques applied in the reconfiguration of distribution systems,” *IEEE Trans. Power Del.*, vol. 21, no. 1, pp. 1735–1742, 2006.

[22] L. W. de Oliveira, S. Carneiro Jr., E. J. de Oliveira, J. L. R. Pereira, I. C. Silva Jr., and J. S. Costa, “Optimal reconfiguration and capacitor allocation in radial distribution systems for energy losses minimization,” *Int. J. Electr. Power Energy Syst.*, vol. 32, no. 8, pp. 840–848, 2010.

[23] A. Zidan and E. F. El-Saadany, “Distribution system reconfiguration for energy loss reduction considering the variability of load and local renewable generation,” *Energy*, vol. 59, pp. 698–707, 2013.

[24] S. S. F. Souza, R. Romero, J. Pereira, and J. T. Saraiva, “Artificial immune algorithm applied to distribution system reconfiguration with variable demand,” *Int. J. Electr. Power Energy Syst.*, vol. 82, pp. 561–568, 2016.

[25] Z. Li, S. Jazebi, and F. de León, “Determination of the optimal switching frequency for distribution system reconfiguration,” *IEEE Trans. Power Del.*, vol. 32, no. 4, pp. 2060–2069, 2017.