Strategic Scheduling in Smart Grids

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Abstract—**With a shorter scheduling horizon, it is easier to handle the system uncertainties in distribution scheduling problem. On the other hand, due to higher cost of some control actions, e.g., tap changing operations, with a short horizon, these high cost control actions may never be justified, even though they could be necessary in the future. With a longer scheduling horizon, the operator have a wider choice and can schedule the tap changing operations to further reduce the total system cost. A multi-period scheduling scheme is proposed in this paper for cost minimization. Different scenarios are generated to model the uncertainties associated with renewable resources, upstream system and system loads. The number of scenarios is then reduced to moderate the computational burden. In the first period, the decision variables should be the same for all scenarios. Only the decisions made for the first period will be applied. For the next periods, this framework should be applied again. In this way, a long scheduling horizon is modeled, the available and forecast data are considered and future decisions are to be made when more accurate data are available. The effectiveness of the method is shown through the case studies.**

Keywords—ant lion optimizer; on-load tap changer; scheduling; smart grids; uncertainties;

I. Introduction

After introduction of dispatchable Distributed Energy Resources (DERs) and other controllable devices, e.g., Static Voltage Regulators (SVRs), Renewable Resources (RRs) and On-Load Tap Changer (OLTC) transformers, to distribution systems, many challenges have arisen in operation and control of these systems. Application of a robust control and management scheme is inevitable in these systems, in order to reduce the chance of conflict between the operations of these controllable devices [1]. Intermittent nature of RRs and the uncertainties associated with system loads, power purchase price and upstream system characteristics should be dealt with to find more optimal scheduling and control strategies and to avoid infeasible solutions for scheduling problem.

With a short scheduling horizon, the effects of system uncertainties are negligible, since the value of the system uncertain parameters can be predicted with an acceptable accuracy. The longer the scheduling horizon, the higher the degree of uncertainty in predictions and therefore, the higher the risk of obtaining sub-optimal or even infeasible solutions. However, with a short scheduling horizon, the high cost control actions, e.g., tap changing operations, may never be justified. The reason lies under the fact that the cost of these control actions is usually higher than the cost of rescheduling the amount of reactive power support of DERs and invertor-interfaced controllable devices and even the cost of active power redispatch. On the other hand, it is quite possible that with a proper strategy for tap position control in a longer horizon, the lower costs can be achieved. In some situations, tap changing operations may also be inevitable in the near future due to the voltage limitations. In these situations, the system operator may be able to make a strategic decision for reducing the system cost by changing the tap position prior to the time that it is really inevitable. In this case, the system future should be known or at least it is necessary to have a vision of this future.

A method for day-ahead and intra-day scheduling procedures was proposed in [2]. The non-linear intra-day scheduling problem was solved by iteratively applying Mixed Integer Linear Programming (MILP). The solution quality was demonstrated in the case studies, but no proof was presented to show that iterative application of MILP problem does not lead to sub-optimal solutions. Scheduling of capacitor banks and OLTCs were usually be conducted for a single day ahead time period [3]. This long period increases the effects of the system uncertainties. In this way, if the system uncertainties are modeled, the system cost will be quite high and if these uncertainties are neglected, there is a fair chance to obtain infeasible solutions.

In this paper, the system future has been modeled in a bundle of scenarios. The scenarios are generated using moment matching technique that was firstly introduced in [4]. The required data are extracted from historical and forecast data. A relatively long multi-period horizon is considered. Each scenario includes load levels at different buses, upstream system characteristics and production levels of RRs as well as the utility active and reactive power purchase price in different periods. The decision variables include the active and reactive power of dispatchable DERs, reactive power of RRs and SVRs, tap positions of OLTC transformers and Capacitor Bank (CB) steps in each scenario in each period. The same decision is taken and will applied for all scenarios in the first period. For the second period the scheduling framework will be applied again. In order to solve the system scheduling optimization problem, Ant Lion Optimizer (ALO) algorithm [5] is adopted.

II. Problem Formulation

A. Uncertainty Handling Technique

Moment matching technique [4] is applied here to generate the system future scenarios. Statistical moments of different orders can be found based on historical and forecast data for the system uncertain variables. The highest order of the statistical moments that is taken into account should be determined according to the level of accuracy required in scenario generation. At least, the average and variance of the system uncertain parameters are required as well as the correlation between these parameters. The objective of the scenario generation subroutine is to generate the scenarios that best match the statistical moments extracted from historical and forecast data. To determine the number of scenarios a compromise should be made between the computational burden and accuracy of the proposed scheduling framework.

B. Stochastic Scheduling Problem

A stochastic formulation is developed in this section for Distribution Management System (DMS). The load level at each load point, active power production of each RR, utility active and reactive power purchase prices and upstream system characteristics in each period are given for each scenario. The upstream system is modeled by the Thevenin voltage and impedance viewed from the primary side of the stepdown transformers. For a system with N_b buses indexed by b, N_{DER} DERs indexed by i, N_{RR} RRs indexed by j, N_{CB} CBs indexed by k, N_{SVR} SVRs indexed by q and N_t OLTC transformers indexed by t, the objective function is given in (1) for N_s scenarios indexed by s and s' and T periods indexed by p. In this objective function, Δ_p is the length of period t. To reduce the computational burden, as p increases, Δ_p can be reduced, since the system uncertainty level increases and also the results obtained for the periods other than the first one are not really applied. The proposed framework is applied again to obtain the scheduling results of the next periods.

The optimization subroutine calculates the active and reactive powers of dispatchable DERs (Pg, Qg), transformers' tap positions (u), reactive power of RRs and SVRs and step of capacitor banks (v) in each scenario in each period within their capacity limits to minimize the system operation cost. Variables u and v are integer. In the objective function, ρ^a and ρ^r are the utility prices for active and reactive powers and generation cost of DER i is given by C_i. Cost of tap and step changing operations for OLTC transformer t and CB k is given in CC_t and CC_k, respectively. The same decisions should be taken for all scenarios in period 1. This has schematically been shown in Fig. 1. This constraint is given in (2). $DV_{s,p}$ is the vector of decision variables for scenario s in period p.

In order to model the cost of discrete control actions, i.e., OLTC transformers' tap changing and capacitor banks' step changing operations, ancillary variables u^* and v^* have been introduced, respectively. These integer variables can easily be calculated using (3) and (4) and are not included in the list of optimization variables that should be found using ALO. Like [6], here, the cost of tap changing operation does not depend on the number of taps that are changed. The same model is applied for CBs.

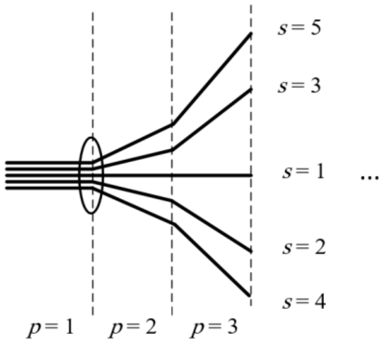

Fig. 1. Decisions made for each scenario in each period.

Remaining capacity of RRs is dedicated to reactive power support (5a) for better voltage control and further loss and therefore, cost reduction. However there are some other constraints on the reactive power support of some certain types of RRs. To limit the harmonic distortion of the current injected by the photovoltaic units, their power factor should be higher than a specified value (5b). In (5b), α^* is the maximum power angle. The reactive power injected by the doubly-fed induction generator (DFIG) units should be higher than a specified value (5c). RR, PV and DFIG are the sets of renewable resources, photovoltaic units and DFIG wind turbines, respectively. The nominal apparent power of the DERs, RRs and SVRs is denoted by S. The capacity limits of other devices is given in (6)-(9). According to the standards, V_b should be within the permissible limits (10). The current of line l is given by I_l and should be lower than the line current carrying capacity (11).

$$\text{Min} \quad \sum_{s=1}^{N_s}\sum_{p=1}^{T}\left\{\begin{array}{l}\Delta_p\left(\rho^a_{s,p}.P_{s,p}+\rho^a_{s,p}.Q_{s,p}\right)+\sum_{i=1}^{N_{DER}} C_i \\ +\sum_{t=1}^{N_t} u^*_{t,s,p}.CC_t+\sum_{k=1}^{N_{CB}} v^*_{k,s,p}.CC_k\end{array}\right\} \tag{1}$$

$$DV_{s,1}=DV_{s',1} \qquad \forall s,s' \tag{2}$$

$$u^*_{t,s,p}=\begin{cases}1 & \text{if } u_{t,s,p}\neq u_{t,s,(p-1)}\\ 0 & \text{if } u_{t,s,p}=u_{t,s,(p-1)}\end{cases} \tag{3}$$

$$v^*_{k,s,p}=\begin{cases}1 & \text{if } v_{k,s,p}\neq v_{k,s,(p-1)}\\ 0 & \text{if } v_{k,s,p}=v_{k,s,(p-1)}\end{cases} \tag{4}$$

$$-\sqrt{S_j^2-Pg_{j,s,p}^2}\leq Qg_{j,s,p}\leq\sqrt{S_j^2-Pg_{j,s,p}^2} \quad \forall s,p,j\in \text{RR} \tag{5a}$$

$$-\tan(\alpha_j^*)Pg_{j,s,p}\leq Qg_{j,s,p}\leq\tan(\alpha_j^*)Pg_{j,s,p} \quad \forall s,p,j\in \text{PV} \tag{5b}$$

$$Qg_j^{\min}\leq Qg_{j,s,p} \quad \forall s,p,j\in \text{DFIG} \tag{5c}$$

$$\begin{array}{l} u_t^{\min}\leq u_{t,s,p}\leq u_t^{\max}\\ u^*_{t,s,p}\in\{0,1\}\end{array} \tag{6}$$

$$\begin{array}{l} v_k^{\min}\leq v_{k,s,p}\leq v_k^{\max}\\ v^*_{k,s,p}\in\{0,1\}\end{array} \tag{7}$$

$$-Q_q^{\max}\leq Qg_{q,s,p}\leq Q_q^{\max} \tag{8}$$

$$-Q_i^{\min}\leq Qg_{j,s,p}\leq Q_i^{\max} \tag{9a}$$

$$\sqrt{Pg_{i,s,p}{}^2 + Qg_{i,s,p}{}^2} \le S_i^{\max} \quad (9b)$$

$$V_b^{\min} \le V_{b,s,p} \le V_b^{\max} \quad (10)$$

$$I_{l,s,p} \le I_l^{\max} \quad (11)$$

Transformers model under OLTC control was provided in [7]. For a single transformer with the tap changer installed at the primary side, this *pi* model is given in Fig. 2, where r is the transformer per-unit turn ratio, Z^n_{sc} is the series impedance of this transformer at nominal turn ratio, i.e., r=1. All the admittances are given in per-unit and it is assumed that the core remains unsaturated. The core loss resistance and magnetizing reactance associated with the nominal turn ratio are given by R^n_c and X^n_M, respectively. This model can easily be applied in power flow studies. For the parallel transformer working under OLTC control, the same model is used. Then, the value of each admittance is the sum of the regarding admittances of all parallel transformer. Since in the proposed framework, the optimization variable regarding OLTC transformer t, is the transformer tap position (u_t), the turn ratio r, should be rewritten as $1+u_t\Delta U_t$, where ΔU_t is the per-unit turn change as the result of one step change in tap position ($\Delta N_t/\Delta N_t^n$).

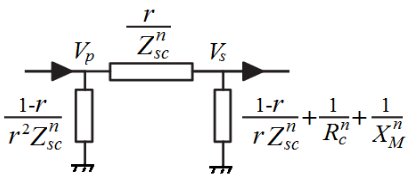

Fig. 1. Transformer *pi* model under OLTC controller.

Voltage-dependent nature of the system loads is also modeled in this paper to show how the system cost can further be reduced by reducing the voltage at substation level and managing the control devices to maintain the system voltages within the standard limits. ZIP model is applied here. The detail of this model can be found in [8]. In case studies, it will be shown how the OLTC control is affected by the load model under the proposed stochastic multi-period scheduling framework.

C. Optimization Technique

The scheduling problem is a mixed integer nonlinear programming problem. Inclusion of the system uncertainties in this problem escalates the computational burden. A heuristic optimization technique can be used to solve the scheduling problem. None of these techniques are guaranteed to converge to a global optimal or perfect solution, but their final solution is optimal enough if their parameters are set appropriately and the problem modeling procedure is skillfully managed. Though the literature of this field is replete with different optimization techniques, as declared in the No Free Lunch (NFL) theorem, there is no decisive and determinative reason for using any specific optimization technique [9]. It can be inferred from this theorem that for a special problem, one meta-heuristic algorithm may show an acceptable performance, but this performance is highly case-dependent even with adjusting the algorithm parameters. In other words, there is no optimization technique that can outperform the other techniques in a wide range of optimization problems.

Here, in order to solve the resultant MINLP, ALO algorithm which is a metaheuristic algorithm is used. The details of this algorithm can be found in [5]. It should be noted that any other heuristic algorithms can be applied along with the proposed formulation to find the feasible and optimal schedule of distribution systems and application of ALO is not a contribution of this paper. For each solution which is generated in successive iterations of ALO algorithm the objective function is calculated using (1). For each scenario, backward forward load flow algorithm [10] is used here to find the voltages and currents in each scenario and each time period.

As mentioned before, it is very important to capture the problem characteristics that may improve the performance of the algorithm and may improve the convergence speed. It is also important to model the optimization problem appropriately. One of the factors affecting the performance of a metaheuristic algorithm is the constraint handling technique. In this paper, in order to handle constraint (2), the same optimization variables are used to introduce the controllers' setting in period 1 for all scenarios. Constraints (5)-(8) and (9a) are introduced to ALO as the lower and upper bounds on optimization variables. Constraints (9b) and (10)-(11) are handled using parameter free penalty functions based on [11]. In the penalty functions, the values of the constraint violations are multiplied by big coefficients (M) to raise the value of the objective function proportional to these violations. Such constraint violation handling technique pushes the infeasible solutions towards the feasible region in the successive iterations of ALO algorithm. However, the big coefficients used to append the penalty functions to the objective function to form the final fitness function should be selected carefully. Selecting a very big M may lead to pure satisfaction of the regarding constraints and selecting a relatively small M may cause sub-optimal solutions. An upper bound can be found for the system cost in each period and each scenario ($F_{s,p}$). It is sufficient to assign a Maximum Constraint Violation (MCV) for each constraint in each scenario in each period. As an example, 0.1 % voltage violation may be acceptable for the system operator. In that case, the MCV of the voltage constraint (MCV_v) would be 0.001 and then, the value of the regarding positive big coefficient (M) can be $F_{s,p}/MCV_{v,s,p}$. In this way, when the optimization is terminated the operator can be sure that this constraint is satisfied or there is no other solution that can further reduce the sum of the penalty functions and the objective function. The MCVs should also be selected according to the constraints' relative importance. For instance, for more sensitive buses, MCV_v should be lower. The MCVs should be lower for the first periods.

III. Numerical Results

The proposed framework is tested on IEEE 33-bus test system. The system loads at different load points and also the network characteristics can be found in [12]. It is assumed that two parallel OLTC transformers connect this distribution system to the upstream network. The data of this two parallel transformers are provided in Table I. A CB, a dispatchable DER, a photovoltaic unit and an SVR are added to the base test system. Table II gives the data of these controllable devices. The DER energy price is 60 €/MWh and the rate of providing reactive power support by this unit is 30 €/MVARh, which is very higher than the rate of providing reactive power offered by the upstream system. The hourly load data can be found in [13] as well as the energy purchase prices in different hours of the day. The price of reactive power provision is 10% of the energy price at each period. The average residential load coefficients can be found in [8]. It is assumed that the photovoltaic unit produces power from 7 AM to 7 PM with the maximum power production of 250 kW at 1 PM. From 6 AM to 1 PM the solar power generation changes linearly from zero to the mentioned maximum power. From 1 PM to 8 PM, the output of this unit changes linearly from the maximum value to zero. Voltage limits are considered to be 0.95 and 1.05 pu. For the sake of simplicity and tractability, for all periods Δ is considered to be 1 hour. It is assumed that the upstream Thevenin voltage changes during the day and this changes usually take place at hours 12, 17 and 22. From 1 to 11, 12 to 16, 17 to 21 and 22 to 24 this voltage is 1, 0.99, 0.98 and 1 pu, respectively. The upstream Thevenin impedance is neglected. The scheduling period (T) is assumed to be 20 hours. It has been assumed that the cost of tap changing operations of the OLTC transformers and step changing operations of the CB are 30 and 10 €, respectively.

TABLE I. SYSTEM TRANSFORMERS

No.	Capacity (MW)	Z^{n}_{se} (pu.)	Rc (pu.)	XM (pu.)	u^{max}	u^{min}	ΔU (%)
1	2	0.006+0.100j	100	95	3	-3	1
2	2	0.006+0.110j	100	96	3	-3	1

TABLE II. OTHER CONTROLLABLE DEVICES

	Capacity (kVA)	Pg^{max} (kW)	Qg^{max} (kVAR)	Other limitations
CB	500	0	500	v^{max}=5
DER	250	250	50	-
PV	250	250	100	α^{max}=35°
SVR	500	0	250	-

The average values (μ) of all uncertain parameters have been given so far. In order to model these uncertainties, a forecast error ($\sigma_{p,\zeta}$) is assigned to uncertain parameter ζ at period p. Beginning from $\sigma_{1,\zeta}$= 0.01$\mu_{1,\zeta}$ (for the first period) this forecast error is increased linearly for the upcoming periods so that for p=11, $\sigma_{11,\zeta}$= 0.02$\mu_{11,\zeta}$. A normal probability distribution is assigned to uncertain parameter ζ at period p with the average and standard deviation of $\sigma_{p,\zeta}$ and $\mu_{p,\zeta}$, respectively.

It has been assumed that for the base period (before applying the proposed scheduling framework), $u_{1,0}$=$u_{1,0}$= 0, $v_{1,0}$=3, Pg^{DER}=0, Qg^{DER}=0, Qg^{PV} =0 and Qg^{SVR} =300 kVAR. For the first study, the change in the problem optimization variables is limited to find the system difficulties. The values of $|\Delta Pg^{DER}|$, $|\Delta Qg^{DER}|$, $|\Delta Qg^{SVR}|$, $|\Delta Qg^{PV}|$, $|\Delta u|$ and $|\Delta v|$ are limited to 100 kW, 50 kVAR, 100 kVAR, 50 kVAR, 1 and 1, respectively.

Fig. 3 shows the best voltage profiles obtained by the proposed method in all the scheduling periods for the most probable scenario and the scheduling horizon beginning from 1 am to 8 pm. Bus 0 is the primary side of the transformers. As can be seen though the tap position is decreased to raise the voltage levels, with limited control capacity, it is not possible to control the voltage within the specified limits for most of the periods (due to the lower voltage limit violations).

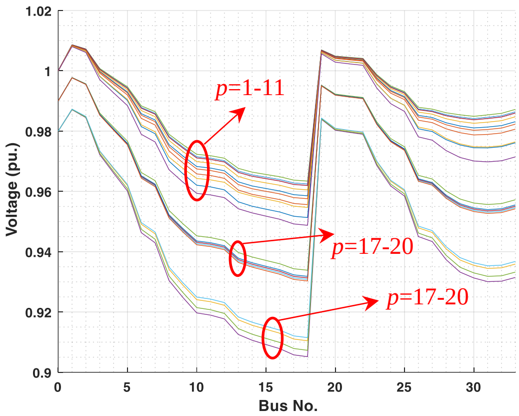

Fig. 3. Voltage profiles (20 hours) for limited control capacity (Case 1).

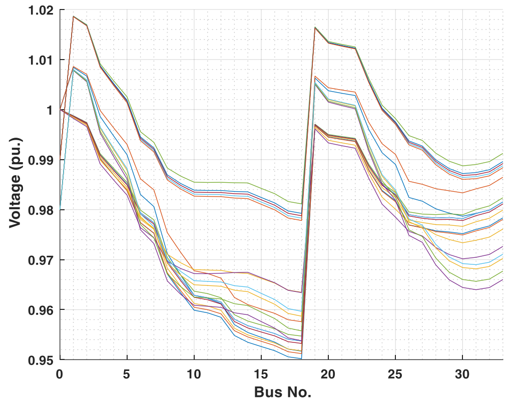

Fig. 4. Voltage profiles (20 hours) with full control capacity (Case 2).

In the second study, the limitations on the control capacities are removed and the controllable variables can be changed within the limits specified in Table II. Fig. 4 shows the best voltage profiles for the scheduling horizon beginning from 1 am to 8 pm. As can be seen, now it is possible to satisfy all the voltage constraints. It is quite interesting that tap changing operation are employed multiple times to reduce the control cost and also to satisfy the voltage constraints.

In order to elaborate on the sides of this subject another study is conducted, in which the proposed framework is applied 24 times to obtain the results of the scheduling horizon for all periods of the day. It should be noted that for each period a separate scheduling problem is solved and the scheduling horizon (T) for this period is 20 hours. One can assume a 20-hour window which is being moved hour by hour to obtain the scheduling results at each hour considering the system future. For some hours, a certain length of this window happens in the next day. It has been assumed that for the next day, all the parameters, e.g., load levels, are the same as those considered for the current day.

Fig. 5 shows the load factor, i.e., the load level at each hour divided by maximum load level during the day, and also the system costs. As can be seen the proposed algorithm is able to find the optimal solution of the scheduling problem since the system costs follows the intraday load variations. It can be seen that the tap position has been changed 5 times to satisfy the voltage constraints and also to reduce the system cost. Fig. 6

shows the upstream Thevenin voltages as well as the OLTC tap positions. At hour 1, the tap position is reduced to increase the voltage at the transformers' secondary side to satisfy level voltage constraint. At hour 3, the tap position is increased back into 0 to decrease the system cost during hours 3 to 9. Since the load levels are lower (comparing to hours 1 and 2), the voltage constraints are still satisfied in these hours. In hours 10 and 11, the load levels are higher than hour 1, but it is not necessary to reduce the tap position to satisfy the voltage constraints, since the utility power purchase price is higher than the price offered by the dispatchable DER for these hours and this justifies power generation using this DER. This reduces the voltage drop across the network lines and therefore, the voltage constraints are satisfied. For the remaining hours, the voltage drop at upstream system leave no other choice but to reducing the tap position to satisfy the voltage constraints during the high load periods. At hour 22, the voltage at upstream network is backed to 1 pu again. The tap position is therefore increased to reduce the system cost.

It should be noted that neglecting the load-to-voltage dependency and also the transformers' core losses, the system cost should be lower for higher voltage levels, i.e., lower tap positions, due to lower network loss. However, in distribution systems load level and transformer core loss decrease as the voltage level is decreased based on [14] and as observed here.

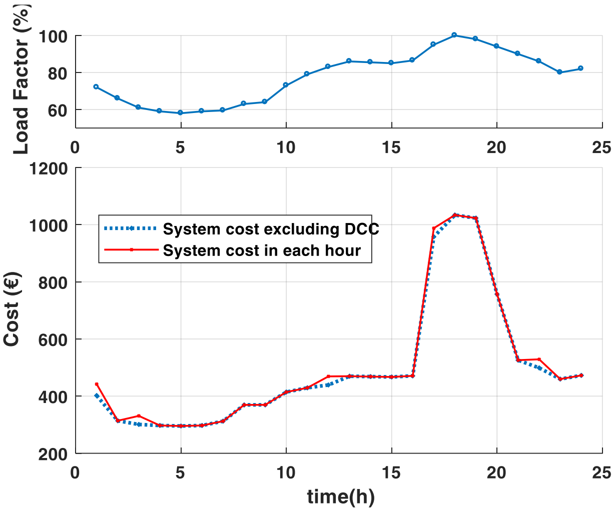

Fig. 5. Load factor and system operation costs.

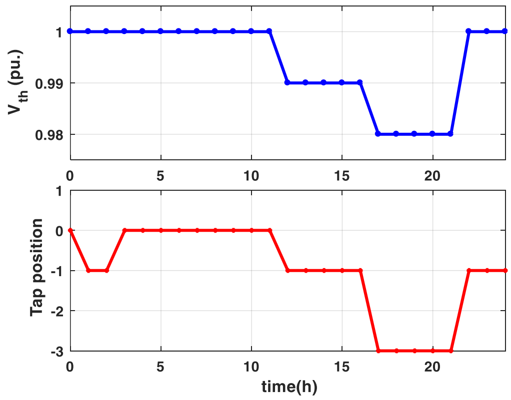

Fig. 6. Upstream Thevenin voltages and OLTC tap positions.

IV. Conclusions

With a short scheduling horizon, it is quite easier to handle the system uncertainties. However, in this way the tap changing operations of OLTC transformers and CB step changes may not be justified. To benefit the advantage of both short and long scheduling horizons a multi-period scheduling framework can be applied. Based on the results of the case studies, the proposed framework can solve the scheduling problem considering the system uncertainties at each period considering the system future. In the test system, the higher tap positions (lower voltage levels) lead to the lower costs. It was also observed that if the load level stays down during a long enough period, tap position can be increased to decrease the system cost. However, the system resources should be controlled to satisfy the constraints.

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