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An Intelligent Hierarchical Voltage Control based on the Dynamic Partition of Control Device Groups

Haomin Ma , Genping Wang, Mei Tao and Dan Lin

Industrial Training Centre, Shenzhen Polytechnic

Abstract. Optimal coordinated voltage control (CVC) for large scale power systems is a hard combinatorial optimization problem with fast response requirements. Intelligent techniques have been widely applied and proved with good performance for hard combinatorial optimization problems. However, with an increase in system scales, the knowledge-based techniques may lack adaptivity meeting enormous dynamics and changes, and the global search techniques cannot meet the quick response of CVC. A hierarchical CVC based on control device groups and an on-line supervised search is proposed. With multi-objective optimization, the control knowledge is obtained from the set of Pareto solutions by which the control devices are grouped into a hierarchical structure of basic, supplementary, and inactive control devices. A set of control knowledge are thus prepared by an off-line search, dynamically adjusted by an on-line search, and saved in a long-term memory. Based on the control knowledge an on-line hierarchical optimal search is applied to provide a quick real-time optimal control. Not only does the control knowledge provide active control devices considered for serious situations, but also works to supervise a global search including the inactive control devices for a non-serious situation. With this scheme, the optimal CVC is fast and adaptive to new situations.

Keywords: Hierarchical control, coordinated voltage control, multi-objective optimization, hierarchical genetic algorithm

1. Introduction

As modern power systems become more and more stressed, voltage instability has become a major concern. As defined by CIGRE and IEEE [1], voltage stability deals with the ability to maintain voltage profiles while being subjected to a disturbance, with the entire system performance remaining intact.

For mid- or long-term voltage instability, a coordinated voltage control (CVC) adjusts various voltage control devices within a wide area and aims to keep voltage profiles of a power system within acceptable levels after system emergencies.

The optimization of CVC is a hard-combinatorial optimization problem with high dimensional, discrete solution space, and in a real-time response requirement. As modern power systems are kept increasing in size, the research efforts of various artificial intelligence techniques have been applied. These can be categorized into two main directions: knowledge-based methods [4,5] and computational intelligence techniques [6-12].

Knowledge-based or rule-based techniques, e.g. expert system [4,5], depending on operational knowledge are advanced in responsibility but challenged by the subjectivity of knowledge and a lack of adaptivity. On the contrary, computational intelligence techniques, including fuzzy logic control [6], artificial neural network (ANN) [7,8], evolutionary algorithms [9,10], and swarm intelligent algorithms [11,12], accumulate and depend on objective knowledge. For fuzzy logic control and ANN, the acquired knowledge is stored as rules or structures which may not meet the great uncertainties once the control system is fully and well trained. For meta-heuristic algorithms, i.e. evolutionary algorithms and swarm intelligence algorithms, a critical conflict rises between low search efficiency and limited search times. Even for the mid- or long-term voltage instabilities concerned in this paper, an optimal search of CVC should be finished within seconds to tens of seconds.

To overcome challenges, there are two main directions of research efforts (Fig.1). For knowledge-based or off-line trained techniques, e.g. expert systems, fuzzy logic control, and ANN, on-line adaptability need to be further explored so that they can meet on-line dynamic changes and operational variations. For meta-heuristic random search techniques, e.g. evolutionary algorithms and swarm intelligence algorithms, the searching efficiency is improved by adjusting the algorithm itself or exploring specified system knowledge to reduce solution space to a certain degree. As the slow convergence speed of the random search techniques cannot be solved fundamentally by adjusting themselves, more researches have been focusing on exploring knowledge of the targeted system by which the search burdens can be reduced.

The main inspiration tries to reduce solution space by partition and decoupling of a power system [13-15]. A distributed control can thus be applied with the decomposition of a power system into several areas according to the geographical or electrical closeness of operation elements. However, the partition techniques for CVC are challenged for their dependent on static analysis. Whatever it depends on the geographical structure, operational experiences, sensitivity analysis, or electrical distances, there is no reflection of the dynamics of a voltage instable emergency.

A new direction is explored in this study. The partition depends on the control device group (CDG) which are basic, supplementary, and inactive control devices. After an evaluation of the system situation, only parts of control devices are adopted for an optimal search. Not the same as the partition of systems, the grouping of control devices is obtained from multi-objective optimization and time-domain simulation where the dynamics are involved.

In this paper, a new hierarchical coordinated voltage control (HCVC) based on a prepared CDG pool is proposed for CVC. The control knowledge is the grouping of control devices according to their control sensitivity for a specified emergency. After off-line multi-objective optimization and grouping of control devices, sets of CDGs of a power system are firstly generated and stored together. Once an emergency happens on-line, the optimal search is applied according to the priorities and efficiency of a CDG.

With the guidance of a CDG, i.e. the priority of control devices, an optimal CVC is realized in a hierarchical structure. The search focuses on the basic control devices for a serious situation that the system will experience a blackout within 30secs. For a non-serious situation, an optimal search is applied hierarchically that the most effort on searching is devoted to the so-called basic control devices, a refinement is applied by investigating into the supplementary control devices, and further improves of control is performed by monitoring and adjusting the previously inactive control devices in the overall system. With these heuristic sets, each level of search by HCVC can be greatly improved.

The organization of this paper is as follows: How we gather and define CDGs is presented in Section 2. The way of exploring control knowledge and then reaching a fast on-line control by HCVC is proposed in Section 3. A demonstration in the IEEE 118-bus system and a discussion about performances of the HCVC are denoted in Section 4. Conclusions are given in Section 5.

2. Control knowledge from multi-objective optimization

The basic innovation of this study is the dynamic partition of solution space with CDGs. CDG is obtained from the optimal solution set searched from multi-objective optimization of CVC. As a model predictive control (MPC) based CVC is applied in this study, system dynamics are thus involved.

In this section, the multi-objective of MPC-based CVC, the searched optimal solution set, and the grouping of control devices are presented.

2.1. Multi-objective Optimization of MPC based CVC

For voltage control, the hybrid differential-algebraic (DA) model of power systems [3] is:

$$\frac{dx}{dt} = f(x, y, z(k)) \tag{1}$$

$$0 = g(x, y, z(k)) \tag{2}$$

$$z(k+1) = h(x, y, z(k)) \tag{3}$$

where x contains the dynamic state variables; y contains the algebraic state variables and $z(k)$ denotes discrete control variables. The system dynamics of (1) relies on dynamic loads.

The technique of CVC defines a control strategy by which a set of control actions of various control devices within a wide area in a power system is adjusted to keep the voltage stability. In this research, full control devices are involved. The optimal CVC finds out a good enough $z(k)$, so that the system output, y, can be kept within a reasonable level considering system dynamics of x.

MPC is an advanced control technology with less dependence on full system models and can handle the nonlinearities and constraints in the CVC problem [14]. MPC has been widely applied for process control in complex industrial systems. Optimal control is obtained from a set of candidate solutions by solving a receding horizon optimization problem according to the past and current system states and parameter settings. Dynamic models and optimization of power systems can be involved in the MPC based CVC [15].

For mid- or long-term voltage instability, a quasi-steady-state (QSS) simulation [16] is used to capture the basic trend of voltage profiles rapidly by neglecting the fast transient of generators, motors, etc.. For QSS simulation, system voltages which are represented by algebraic state variable y are instantaneously changed due to the changes of control variables $z(k)$ and load dynamics of x. The control devices, i.e. on-load-tap-changers (OLTC), capacitors, and load shedding, which can set reference values of a wide area of a power system are discrete control variables represented by $z(k)$.

For modern power systems, voltage control is a multi-objective problem in considering operational, economic, and environmental preferences. Regulating system voltages is the basic objective of optimal CVC. However, multiple objectives should be considered, e.g. frequent switches of control devices are not preferred considering the cost of equipment maintenance and service reliability, load shedding should always be the last effort for control, etc..

The objective of minimization of control actions is considered with the basic target of tracing reference voltages,

$$J_{\sum v} = \min \sum_i \sum_t \left| V_{i,t} - V_{i,ref} \right| \tag{4}$$

$$J_{act} = \min(w_t \sum_t m_t + w_c \sum_c m_c + w_l \sum_l m_l) \tag{5}$$

where $V_{i,t}$ denotes the voltage of bus i at time t; $V_{i,ref}$ denotes the reference voltage at bus i; m_t, m_c and m_l are the movement steps of OLTCs, capacitors, and load shedding respectively; w_t, w_c, and w_l are the weights which reflect the control preferences of different control devices.

For multi-objective optimization, a solution is evaluated by the concept of domination. With two objectives, the solution y is said to dominate the solution x when one or two objective values of y is less than that of x and none of them is greater than that of x. If a solution is not dominated by any other solutions within the solution space, that solution is said to be a Pareto solution. For large-scale complex systems, the real Pareto solutions may not be found in a reasonable time. As a result, the non-dominated solutions (NDSs) of all visited feasible solutions are used instead of Pareto solutions.

With the multi-objective optimization of MPC-based CVC, the system knowledge can be investigated from the set of non-dominated solutions by tracing reference voltages and various objectives. With two objectives of (4-5), a set of non-dominated solutions exist showing how they tradeoff with each other in meeting different control preferences.

2.2. Knowledge from NDS Set

The control knowledge is explored from NDS sets. The NDS of $J_{act} = i$ is the most effective control of recovering bus voltages among all visited solutions using i control actions. By tracing the values of J_{act} of NDSs, a queue of effective control solutions can be obtained.

A further study with variations of operational points and emergencies shows that there exist some common characteristics among control solutions of the NDS set. These characteristics are expressed with a demonstration of an example case.

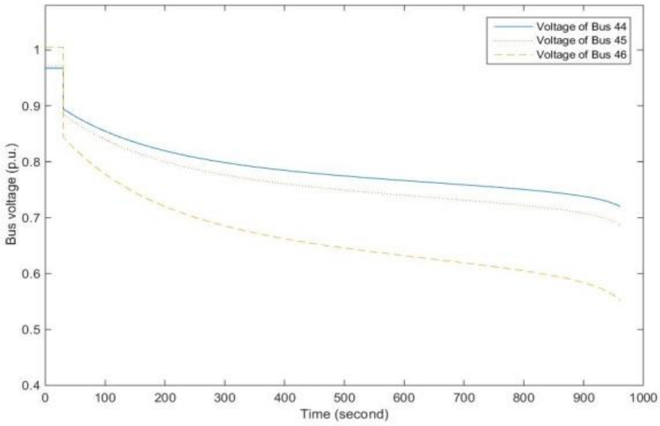

Fig.1 Fault of Tripping Generator 46 in the IEEE 118-bus system

A fault of Tripping Generator 46 in the IEEE 118-bus system is used for demonstration. The original operational point of the IEEE 118-bus system is not close to the stability limits. The example fault won't trigger blackout and only has a few NDSs. To provide a more representative scenario of voltage instability, the operational point is changed by multiplying the reactive power of loads to 1.5 times their original values. Bus voltages drop to lower values and experience a collapse 900 seconds after the fault happens (Fig.1).

The control interval is set as 30s to fit the activation time of OLTC. After a long-term global search by meta-heuristic algorithms, say standard genetic algorithm (GA) [17], optimized actions of various control devices are obtained. There is a total 19 of NDSs (Fig.2) for the first control interval of MPC-based CVC.

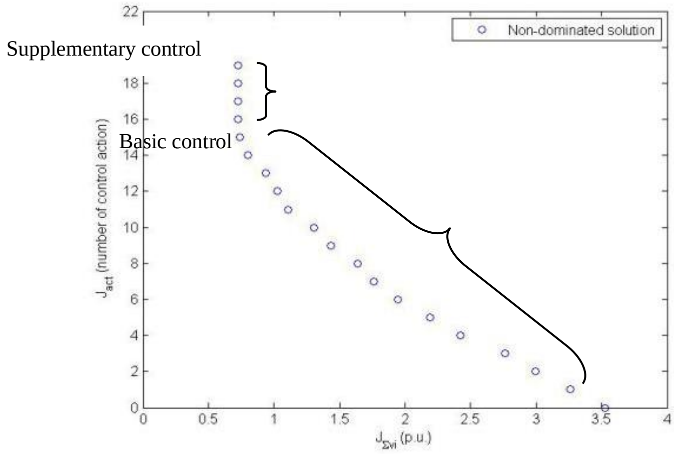

Fig.2 NDSs of Fault of Tripping Generator 46

The objective values and corresponding controls of NDSs are listed in Table 1. Note '1' and '-1' means the control device is increased or decreased one step from its original value. Capacitor 44, 45, 46 and 48 represented as C44, C45, C46, and C48 are used in NDSs of $J_{act} = 1$ to 16. OLTCS of T37, T65, and Capacitor C34 are used in NDSs of $J_{act} = 17$ to 19 addition to control actions of $J_{act} = 16$.

Table.1 NDSs of Fault of Tripping Generator 46

J_{act}	$J_{\Sigma v}$	C44	C45	C46	C48	T37	T65	C34

19	0.7275	1	4	7	4	-1	-1	1
18	0.7276	1	4	7	4	-1	-1	
17	0.7277	1	4	7	4	-1		
16	0.7279	1	4	7	4			
15	0.7426	1	4	7	3			
14	0.8007	1	4	7	2			
13	0.9392	1	4	6	2			
12	1.0234	1	4	6	1			
11	1.1070	2	3	6				
10	1.3026	3	2	5				
9	1.4353	3	2	4				
8	1.6414	3	2	3				
7	1.7584	4	2	1				
6	1.9449	4	2					
5	2.4256	4	1					
4	2.7630	3	1					
3	2.9925	2	1					
2	3.2629	2						
1	3.5252	1						

We can find interesting and useful characteristics of NDSs. Generally, the priorities of control devices are different while their participation among NDSs is constantly. Some detailed analysis is presented below:

(1) ***Effective control***: Among all the feasible solutions of $J_{act} = i$, the i^{th} NDS is the most effective control solution where it has the least value of $J_{\sum v}$. The set of control actions of each of the NDS is called an effective control. The effective control of $J_{act} = 6$ is $\{C44+4, C45+2\}$ which is increasing four steps of Capacitor 44 and increasing two steps of Capacitor 45 from their original values. Compare to all the other control solutions which has $J_{act} = 6$, this effective control, i.e. $\{C44+4, C45+2\}$, can reach the least vale of objective, $J_{\sum v}$.

(2) ***Active control devices***: The involved control devices in NDSs are much less than the number of NDSs. There are 19 non-dominated solutions and only 7 control devices are used for this example fault. It is also much less than the total number of control devices in the full system, e.g. there are 9 OLTCs, 14 capacitors, and 91 load sheddings. Some control devices are more sensitive than others for a specified fault. Control devices appeared in NDSs are named as *active control devices*.

(3) ***Grouping of control devices***: Once a control device participates in a NDS of $J_{act} = i$, it always appears in NDSs which have J_{act} greater than i. We can have a queue of control devices reflecting the priority of participation. The queue of participation is {C44, C45, C46, C48, T37, T65, C34}. The participation of control devices is not always constant that a control device appears in the NDS of $J_{act} = i$ may not be used in all the NDSs of $J_{act} > i$. But it won't challenge the participation of the control device.

(4) ***Basic and supplementary control devices***: The control efficiency can be expressed in terms of the sensitivity of $J_{\sum v}$ to a control solution. Effective control of NDSs with lower values of J_{act} are more sensitive in the recovery of bus voltages, e.g. NDSs with $J_{act} = 1$ to $J_{act} = 15$ in Fig.3, where the objective of $J_{\sum v}$ can be greatly improved by one more step of control. We assume a threshold of an improvement of $J_{\sum v}$ as 0.05p.u., i.e. $\Delta J_{\sum v,i} > 0.05 p.u.$. For the rest NDSs, $\Delta J_{\sum v,i}$ are less than 0.001p.u.. Accordingly, the active control devices can be separated into two groups that some of them provide much control sensitivity for adjusting bus voltages while the rests can be used for refinement. Accordingly, C44, C45, C46, and C48 which are involved in NDSs with $J_{act} = 1$ to $J_{act} = 15$ are within a group of basic control devices, and T37, T65, C34 are within the group of supplementary control devices.

Generally, for the 19 NDSs of the fault of Tripping Generator 46 in the IEEE 118-bus system, there are 19 effective controls, 7 active control devices where 4 of them are basic control devices and the rest 3 are supplementary control devices.

2.3. Grouping of control devices

Based on the analysis in Section 2.2, the NDS sets always appear to show the same characteristics: (1) Few active control devices with a range of their possible movements are used in the NDS set. These control devices are gathered and named as active control devices whereas the remaining control devices are with inactive control devices. (2) The sensitivity of bus voltages to each effective control changes. With the increasing J_{act}, the efficiency of effective control is reducing. (3) Some active control devices contribute to greatly improve system voltages whereas the rest can be regarded as a refinement for adjusting voltages.

It is common knowledge that a lack of reactive power balance within an area of a power system may trigger a voltage instability problem. We usually regard reactive power balance as a local property. As a result, some of the control devices are more active than others in adjusting the reactive power of the faulted area.

According to our studies of different power systems, the differences among control sensitivity of effective control devices are even larger with increasing power system scale. This appears mainly due to the unbalance of the arrangement of control devices such that the distances between control devices and the failure element are quite different.

In this study, the control knowledge from NDS sets is acquired that control devices are grouped according to the sensitivities to system voltages. A threshold of control sensitivity needs to be defined by which the basic control devices and the supplementary control devices can be identified. The value of the threshold can be adaptive to the situation of the system and may vary with faults.

A careful strategy for the selection of the threshold setting can further improve the control performance of the optimal CVC. However, it is beyond the scope of this paper given the limitation of space. A fixed value of 0.05p.u. is used as the threshold for the example fault. The control devices involved in NDSs which have $\Delta J_{\sum_v} > 0.05 p.u.$ are grouped. The *basic control devices* are more active in voltage adjustment (Fig.3). The effective control devices just involved in the remaining NDSs are named as *supplementary control devices.* After a fault happens, a large improvement of system voltages can be reached by the basic control devices whereas a fine adjustment is provided by the supplementary control devices. For each fault, the control knowledge is a CDG in which control devices are separated into three groups of basic, supplementary, and inactive devices.

However, power systems are dynamic with changing operational points and even the system structures. Controls that are not included in knowledge may be required when a more serious situation happens. Or, few control movements may be involved in a less serious situation. The adaptability of CVC can be further improved if the controls which are not used in NDSs are also considered.

3. Hierarchical CVC based on CDGs

As we discovered that only part of the control devices may be involved in an emergency voltage control, a HCVC is proposed considering these control sensitivities. An improved GA, hierarchical GA (HGA), which has a hierarchical structure of chromosomes is applied for optimal search.

3.1. Hierarchical search by HGA

GA is one of the evolutionary algorithms which was firstly proposed by Holland [17]. It is inspired by the evolution theory and realized in iterations of some basic search operators, i.e. selection, crossover, and mutation. Based on standard GA, there are many advanced GAs each of which has its' unique advantages. For example, Jumping Gene GA [18] increases the possibilities of creating new connections among genes, while NSGA II [19] is quick in tracing Pareto solutions for multi-objective optimization problems.

It's a common sense that there are groups or hierarchical structure of genes. Some genes in a chromosome are grouped and can be enabled or disabled by one or more other genes in a chromosome. A hierarchical GA (HGA) [20] is thus proposed in which some of the genes are dominated by genes named control genes.

This hierarchical structure of chromosomes gives a more sophisticated organization of genes and thus depends on a systematic understanding of the controlled system and needs a coordination of system knowledge. Its' special structure has made it hard to be fully and well explored and there have no many applications of HGA [21,22] since it was first proposed in the last century. However, according to the control knowledge of CVC analyzed in Section 2, it can be aptly applied to realize a hierarchical control.

GAs are a set of population-based algorithms that the gained knowledge is contained, past and, gradually improved among generations. The calculation processes of HGA is the same as a standard GA.

The difference between the HGA and the standard GA only lies in the formation of the chromosome. A HGA has multiple levels of control genes in a hierarchical structure. The bottom level of controlled genes is named as parametric genes which gives the parameter of control devices. A set of parametric genes are governed by the control genes, which is governed by the second-level control genes, and so on.

To indicate the activation of the control genes, an integer "1" is assigned for each control gene that is being ignited where "0" is for turning it off. Once "1" is signaled, the associated parameter genes due to that particular active control gene are activated in the lower level structure [20].

In this paper, the HGA together with the control knowledge of CDGs is adopted for an optimal CVC. The CDGs are used to define the dominating relations among genes.

3.2. Control Knowledge Base

Being one of the modern heuristic optimization techniques, an online real-time search by HGA cannot meet the limited search time of optimal CVC. A sophisticated knowledge from the power system may provide guidance and greatly speed up the optimal search.

For power transmission network, voltage instability is triggered by a lack of or unbalance of reactive power. Because of the localization characteristic of reactive power, an emergency voltage control is thus sensitive to the closeness of control devices. It is also proved in this study. An analysis of knowledge from multi-objective optimization shows that the most effective control devices are usually geographically close to the emergency area. A CVC should focus on the close area of an emergency and at the same time monitor and adjust controls of both the close and remote areas.

The definition of closeness is not an easy task as voltage stability concerns non-linear discrete dynamic systems. The research in Section 2 shows an alternative way that we can explore the active control devices instead of the close control devices. Thus CDGs of a set of emergencies are prepared and stored in advance. As a result, an on-line optimal search by HGA based on the control knowledge can be greatly improved.

For large scale power systems, emergencies which may trigger a voltage instability can be numerous and unpredictable. It is impossible to prepare knowledge to meet all situations. Based on assumption that the active control devices of an emergency are always graphically close to it, two emergencies close to each other may share most of their active control devices. Thus, a preparation of knowledge needs to cover all of the geographical places of the power system.

In this study, tripping of a generator for all generators and tripping of a transmission line of all lines are studied off-line for knowledge preparation. Each of the emergency is triggered in the system. A standard GA is applied for a long-term search to get the set of non-dominated solutions. As there are no time limitations for this off-line search, a large population with many rounds of search are preferable to trace the real Pareto front. We use a population of 200 with a maximum of generation of 200 and 10 rounds of optimal search.

The CDGs saved for HCVC only concerns the priority of control devices. For the example fault of Tripping Generator 46 (Table.1), the knowledge is,

$$Kwl = \{C44, C45, C46, C48, T26, T65, C34\}$$

For a real-time application, the possible movements of a control device depend on its' current states and rang of admitted control steps. Based on the knowledge and a defined threshold of $\Delta J_{\sum_v}$, e.g. 0.05p.u. for the example fault, active control devices are divided into two groups, the basic control devices, and the supplementary control devices. All the rest control devices are in the group of inactive control devices. 107 control devices for this IEEE 118-bus system are inactive control devices. All control devices are partitioned into three groups (Fig.3).

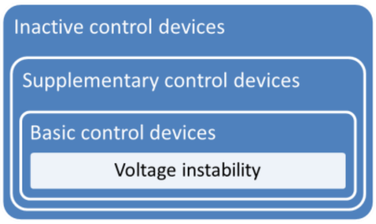

Fig.3 Three groups of control devices

To provide a knowledge basis for all possible voltage instability situations, a full set of CDGs is prepared (Table.2) in advance. As knowledge of tripping all transmission lines is studied, any emergency happens on-line can find its' geographically close emergencies in the knowledge base.

Table.2 Knowledge Base

No.	Fault	Basic control device	Supplementary control device
1	Tripping of G1	CtrlB1,1,CtrlB1,2,...	CtrlS1,1,CtrlS1,2,...
...	...	...	...
m	Tripping of Gm	CtrlBm,1,CtrlBm,2,. ..	CtrlSm,1,CtrlSm,2,...
i+1	Tripping Line1	CtrlBm+1,1,CtrlBm +1,2,...	CtrlSm+1,1,CtrlSm+1,2,...
...	...	...	...
m+n	Tripping Linen	CtrlBm+n,1,CtrlBn, 2,...	CtrlSm+n,1,CtrlSn,2,...

3.3. HGA for Hierarchical CVC

Based on one CDG, an optimal search for MPC-based CVC is realized by HGA that the chromosomes are in a hierarchical structure and different search strengths are applied for active and inactive control devices. The search effort among three groups of control devices should reflect the scheme that: 1) most search effort is applied to the search of basic control devices; 2) refinement of control is reached by the search of supplementary control devices; 3) a possible improved control is visited by a further investigation of inactive control devices.

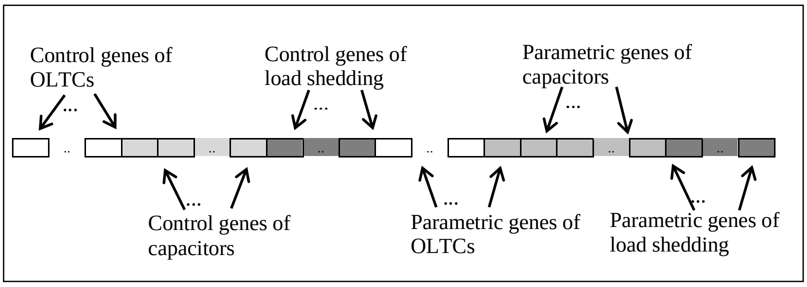

Fig.4 Chromosome structure of HGA

The chromosome structure of HGA is defined as in Fig.4. The control genes of OLTCs, capacitors, and load shedding are binary where the value of "0" and "1" will disable and enable the according control devices. For the parametric genes of OLTCs, the possible values of an OLTC are -1, 0, and 1 as they can only move one step from their original values. The parametric genes of capacitors and load shedding have integer values of 0 to k where "k" is the maximum move steps of the control device.

When an emergency happens on-line, the seriousness of the fault is evaluated in the first place. The saved active control devices of close emergencies is then identified from the knowledge base. Close emergencies are defined as the failure of elements that are connected on the same bus and were studied off-line. Control knowledge of close emergencies are gathered and the control devices are grouped as basic control devices, supplementary control devices, and inactive control devices.

After evaluation, a serious situation is identified if the system experiences a blackout in the coming control interval. Otherwise, it is in an unserious situation. The CVC is thus realized hierarchically with different search strengths. An optimal search only considers the basic control devices that a quick search is applied for a serious situation. If it is an unserious situation, the search effort among three groups of control devices is arranged that 1) a good enough control, $Ctrl_{Level1}$, is provided by the search of basic control devices; 2) refinement of $Ctrl_{Level2}$ is reached by an expansion search to involve supplementary control devices; 3) a possible improved of $Ctrl_{Level3}$ is visited by a further investigation of inactive control devices.

To meet the three levels of optimal search, the search operators of crossover and mutation of HGA is specifically defined. The process of crossover and mutation is only applied to the part of the parametric genes of the chromosome where the control genes are not changed throughout each level of optimal search. This strategy ensures that the priority of control devices is always reflected in the chromosome level and won't be changed during the optimal search.

For the stopping criteria of HGA, the optimal search of each level is stopped when the searched solution can meet the control preferences which are a limitation of search times or acceptable values of bus voltages. Only the optimal search of basic control devices is mandatory where the other two levels of search are optional if the stopping criteria are not reached.

One of the searched NDSs is applied to the system for control. Otherwise, the solution space is expanded, and a further search is applied to the next level of solution space. The calculation steps of the HCVC are as follows:

Step 1) Evaluation of emergency: According to current states and the system model, a prediction of the coming control interval is obtained. If there is a blackout, it is a serious situation. Otherwise, it is identified as an unserious situation.

Step 2) Setting parameters and the stopping criteria: The number of population and maximum generation of optimal search is set for three levels of search. The stopping criteria are defined by a time limitation of search and a desirable value of tracing reference voltages.

Step 3) Control knowledge acquisition: When a fault happens in the system, it is identified by its location and the failed element. Close emergencies are identified. Their control knowledge which are sets of active control devices are acquired from the knowledge base.

Step 4) Obtain the group of control devices: The active control devices are divided into basic control devices and supplementary control devices according to the threshold of control sensitivity of $J_{\sum_v}$. All control devices are divided into three groups which are basic, supplementary, and inactive control devices.

Steps 5) Search the basic control devices: The solution space is defined by basic control devices. The chromosome of HGA is accordingly constructed that only the control genes of the basic control devices are set as "1". An HGA search is applied within this solution area. A set of NDSs is obtained.

Steps 6) Check the stop criteria: If it is identified as a serious situation, go to Step 10). For an unserious situation, the stopping criteria set in Step 2) are checked. If one of the stopping criteria is satisfied, go to Step 10); Otherwise, go to Step 7).

Steps 7) Expend search area to the supplementary control devices: The candidate feasible solutions of search are extended to the solution area which includes the supplementary control devices. Control genes of the basic and supplementary control devices are with the value of "1" where the rests are with the value of "0". After the heuristic optimal search, a set of NDSs is obtained.

Steps 8) Check the stop criteria: If one of the stop criteria is satisfied, go to Step 10); Otherwise, go to Step 9).

Steps 9) Expend search area to the inactive control devices: The solution space is expended to the full area including all feasible solutions by enabling all parametric genes. After the heuristic optimal search, a set of NDSs is obtained.

Steps 10) Apply control solution: The best solution which has the minimum value of $J_{\sum_v}$ is selected from the searched NDS set and applied to the power system.

Steps 11) End program.

4. Simulation Results

Two example emergencies in the IEEE 118-bus system are used to verify this newly developed HCVC. First, the emergency control of Tripping Generator 46 demonstrates the control performance meeting operational point variations. Second, an emergency of Tripping Generator 18 and Tripping Generator 19 at the same time is denoted for unexpected situations for which no readily stored knowledge can be explored from the knowledge base.

Before an online application, two sets of parameters need to be defined:

i) ***Parameters of optimal search***: The population and the maximum generation of three levels of optimal search need to be defined. Generally, the most search effort is applied to the solution area defined by the basic control devices. However, a fast response needs to be considered for this stage in case of serious situations. A refinement search is provided to the solution area defined by the supplementary control devices. An improving search is not compulsory within the remaining solution space including inactive control devices.

In this example case, there are only four basic control devices. a population of POP=20 and maximum generation of GEN=10 is enough to visit most solutions involving basic control devices. It takes about 3s for each run of search with Matlab and an Intel 3.4 GHz processor. The POP=20 and GEN=20 are applied for the search of involving supplementary control devices as this level of the search may involve most of the possible solutions. This part only takes about 6s. The POP=20 and GEN=20 is applied for the search of full solution space involving inactive control devices. It also takes about 6s. Considering the size of the solution area defined by inactive control devices, only a few parts of it can be visited to keep a possibility of improvement.

ii) ***Stopping criteria***: The optimal search needs to be stopped by 30s if there is no blackout within the predicted control interval. If a blackout will happen within the predicted control interval, a feasible control should be applied to the system as soon as possible. For this example case, the total time required by three levels of optimal search is not conflicting with the time limitation of search which is the 30s. Considering that a more expanded search that can visit more candidate solutions is preferred.

a) Control of prepared emergency

For the example fault of tripping Generator 46, there are 19 NDSs searched for the tested operational point to which the reactive power of loads is multiplied by 1.5 times of their original values. As the optimal solutions were prepared in the knowledge base, active control devices of the tested fault of tripping G46 can be obtained.

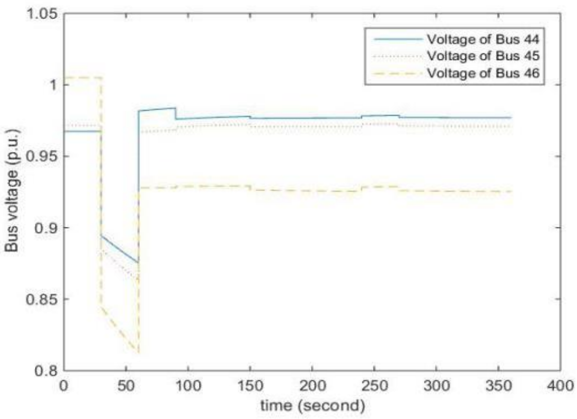

Fig.5 HCVC of Fault of Tripping Generator 46

After the control of HCVC, the voltage deviation caused by Tripping Generator 46 can be recovered to desirable values with very fast system responses (Fig.5). It takes about 15s of each run of an optimal search for one control interval.

To evaluate the search capability of HCVC, a search among off-line prepared effective controls is used to compare with that of HCVC. For this fault, we found 19 NDSs and thus there are only 19 effective controls. It can be quick to visit all of them for an online search.

The solution space defined by active control devices of HCVC is increased compared with that of the searched NDS set in which control devices have fixed control steps. This is because the HCVC is to some extent sacrificing its search efficiency to the adaption of optimal search. As the NDS set is searched on a fixed operational point, it may not be the best when there are variations of operational or even structural changes. The knowledge of HCVC may increase the size of the defined solution space, but it provides more adaptability of control at the same time.

b) Control of unexpected emergencies

To simulate an unexpected situation, two generators of G18 and G19 are tripped at the same time. The system won't reach a blackout but is kept at lower bus voltages.

As two faults of Tripping G18 and Tripping G19 were studied off-line, the control knowledge is listed in Table.4. These two elements are close, the knowledge shares most of their active control devices.

TABLE.4 CONTROL HEURISTICS OF TRIPPING ELEMENTS ON BUS 18

Fault	Basic control device	Supplementary control device
Tripping G18	C45, T81, T30, T65	C79
Tripping G19	C45, T81	C83, T65

When an emergency happens, that G18 and G19 tripping at the same time, the HCVC is applied for control based on the knowledge of Tripping G18 and Tripping G19. The basic and supplementary control devices of these two emergencies are gathered. We use the same search parameters and stopping criteria.

An optimal search by HCVC is thus applied. The control performance is in Fig.6. The voltage profile can be kept at desirable values with a fast response.

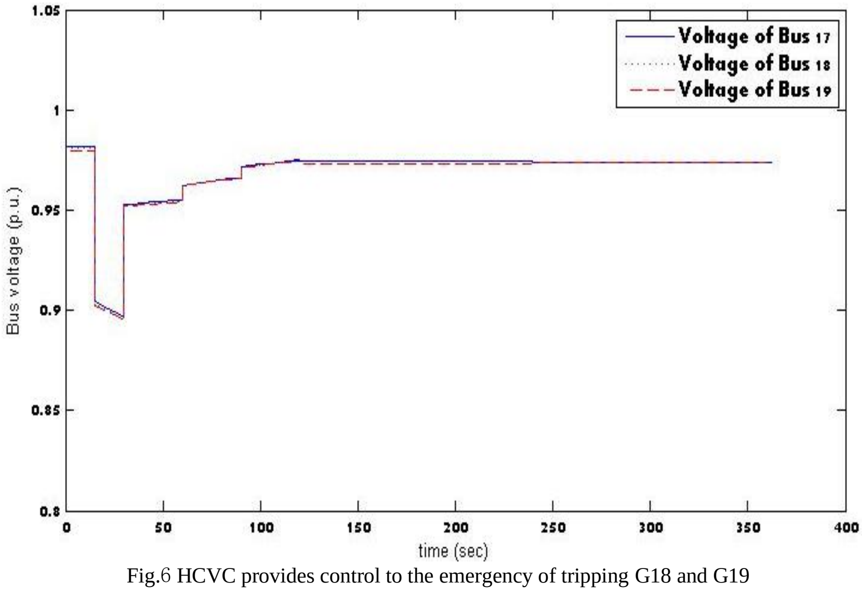

Fig.6 HCVC provides control to the emergency of tripping G18 and G19

Based on control knowledge, the search space of an online search by HCVC is much reduced. The online search by HCVC provides a quick and efficient response for operational point variations and even unexpected emergencies.

Generally, there are two main contributions of this research:

1. A new system partition technique is explored that control devices are grouped according to the control sensitivity. The basic, supplementary, and inactive control devices are gathered and saved for an emergency. Based on control device groups, the solution space for online search can be dramatically reduced to an extremely limited area.

2. The control sensitivities of control devices are obtained by a newly proposed method. First, CVC is considered a multiobjective optimization problem. As a result, a set of NDSs can be searched for each emergency after a long-term random search. Second, the activities of control devices are acquired by queuing the NDS set. The searched knowledge is objective, and the system dynamics are involved at the same time.
3. Based on control knowledge of CDGs, any emergency, etc. an expected situation with fully prepared knowledge or an unexpected situation with no prepared knowledge, has geographically closed knowledge to be explored. Not only is the control knowledge clear and easy to be prepared off-line, but also reliable and robust to be used online.

5. Conclusion

A new HCVC is proposed in this paper. Based on system knowledge of a partition of control devices, an online optimal CVC is realized in a hierarchical structure of three levels of search. According to the sensitivity of tracing system voltages, the control devices are partitioned into three groups as basic, supplementary, and inactive control devices. The main search efforts are applied to the basic control devices whereas the supplementary and inactive control devices are also visited to provide refinement and improvement of control. The HCVC is a fast and effective control strategy that is more adaptive to the system dynamic changes.

6. References

[1] P. Kundur, J. Paserba, S. Viter (2003) Overview on Definition and Classification of Power System Stability, Quality and Security of Electric Power Delivery Systems, CIGRE/IEEE PES International Symposium. https://doi.org/10.1109/QSEPDS.2003.159786

[2] A.M.Azmy (2007) Optimal Power Flow to Manage Voltage Profiles in Interconnected Networks Using Expert Systems, IEEE Trans. on Power Systems 22(4):1622-1628

[3] V. Meza, E. Perez, J.E. Tobon (2019) Knowledge-based Decision Support Tool for Voltage Monitoring and Control: A Proof of Concept, 2019 FISE-IEEE/CIGRE Conference, https://doi.org/10.1109/FISECIGRE48012.2019.8984969

[4] M.V. Santos, A.C. Zambroni de Souza, B.I.L. Lopes, D. Marujo (2015) Secondary voltage control system based on fuzzy logic, Electric Power System Research 119:377-384

[5] P.N. Tekwani, A. Chandwani, S. Sankar, N. Gandhi, S.K. Chauhan (2020) Artificial Neural Network-based power quality compensator, International Journal of Power Electronics 11(2), https://doi.org/10.1504/IJPELEC.2020.105151

[6] H. Cai, H. Ma, D.J. Hill (2020) A Data-Based Learning and Control Method for Long-term Voltage Stability, IEEE Transactions on Power systems 35(4):3203-3212.

[7] W.S. Sakr, R.A. EL-Sehiemy, A.M. Azmy (2017) Adaptive differential evolution algorithm for efficient reactive power management, Applied Soft Computing 53:336-351

[8] H.Ma, D.J.Hill (2018) A fast local search scheme for adaptive coordinated voltage control, IEEE Trans. on Power Systems 33(3):2321-2330

[9] K. Medani, S. Sayah, A. Bekrar (2018) Whale Optimization Algorithm Based Optimal Reactive Power Dispatch: A Case Study of the Algerian Power System, Electric Power Systems Research 163(B):696-705

[10] J. Polprasert, W. Ongsakul, V.N. Dieu (2016) Optimal Reactive Power Dispatch Using Improved Pseudo-gradient Search Particle Swarm Optimization, Journal of Electric Power Components and Systems 44(5):518-532

[11] S. R. Islam, D.Sutanto, K.M. Muttaqi (2015) Coordinated decentralized emergency voltage and reactive power control to prevent long-term voltage instability in a power system. IEEE Trans. On Power Systems 3(5):2591-2603

[12] H. Shahbazi, F. Karbalaei (2020) Decentralized Voltage Control of Power Systems Using Multi-agent Systems, Journal of Modern Power Systems and Clean Energy 8(2):249-259

[13] H.Sun, Q.Guo, B.Zhang, W.Wu, B.Wang (2013) An adaptive zone-division-based automatic voltage control system with applications in China. IEEE Trans. on Power Systems 28(5):1816-1828

[14] E.F. Camacho, C. Bordons (2007) Model Predictive Control, 2nd edn. Springer-Verlag, London, pp 1-4.

[15] Dragana H.Popovic, David J.Hill, Qiang Wu (2002) Optimal Voltage Security Control of Power Systems. Electrical Power and Energy Systems 24:305-320

[16] T.Van Cutsm, M.E.Grenier, D.Lefebvre (2006) Combined Detailed and Quasi steady-state time simulations for large-disturbance analysis. International Journal of Electrical Power & Energy Systems 28(9):634-642

[17] J.H. Holland (1992) Genetic algorithms. Scientific American, pp 66-72

[18] T.M.Chan, K.F.Man, S.Kwong, K.S.Tang (2008) A Jumping Gene Paradigm for Evolutionary Multiobjective Optimization. *IEEE Trans. on Evolutionary Computation* 12(2):143-159

[19] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan (2002) A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans. on Evolutionary Computation 6(2):182-197

[20] K.F.Man, K.S.Tang, and S.Kwong (1999) Genetic Algorithms. Springer-Verlag London Limited

[21] H. Wang, S. Kong, Y. Jin, W. Wei, K.F. Man (2005) Multi-objective hierarchical genetic algorithm for interpretable fuzzy rule-based knowledge extraction. Fuzzy Sets and Systems 149, No.(1):149-186

[22] J. Yeh, J.C. Fu (2008) A hierarchical genetic algorithm for segmentation of multi-spectral human-brain MRI. Expert Systems with Applications 34(2):1285-1295