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Fast Adaptive Control Against Voltage Instability

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Abstract

Adaptive coordinated voltage control provides coordination of various devices within a wide area and adapts to the changing dynamics of power systems subjected to a series of faults. A new adaptive control is proposed for coordinated voltage control in this paper. The off-line training and on-line learning is used to acquire system knowledge. Accompanied by the system knowledge stored in a long-term memory, the on-line search and flexible control can perform a fast and effective control to prevent voltage instabilities.

The simulation results for the IEEE 39 bus and 145 bus systems shows its efficiency. The comparison between controls of these two systems proves that the reduced solution space is not necessarily increased with the system scale.

I Introducation

With the increasing pressure for remote generation (due to air quality requirements), energy efficiency, renewable energy generation and interconnection between grids, voltage instability has been one of the main concerns of the modern power industry in recent decades.

Optimal coordinated voltage control (OCVC) providing optimized discrete control variables has been developed as a solution to providing voltage stability using several control action types. Mathematically this becomes a complex combinatorial optimization problem. Power systems are highly dynamic nonlinear systems. Thus it is difficult to find an optimal solution by which many reactive power controllers within a wide area are adjusted in a coordinated and timely manner so that the system can be kept from voltage instability after an emergency happens.

Research in OCVC mainly falls into two main algorithmic categories: 1) evolutionary algorithms and their related improved techniques [1-4]; 2) knowledge based techniques [5-7]. Generally, there are three main difficulties: i) the search space increases exponentially with the number of controllers; as a result, global and random search may not be efficient for a large scale power system; ii) the operational points and controller priorities vary from time to time, so prepared knowledge loses its effectiveness; iii) a quick system response is required; so a slow convergence speed of methods such as random search is not adequate.

Evolutionary techniques have their inherent ability for learning and can accumulate knowledge themselves. But this learning skill is with low efficiency without additional instructions. On the other hand, knowledge based techniques can provide fast response. But they will not be able to follow the dynamic changes of power systems without a learning ability.

This paper explores a new adaptive way to perform OCVC. The system knowledge is firstly prepared off-line. This knowledge is exploited to reduce the search space and thus guide an efficient on-line optimization. In turn, the newly obtained results are accumulated as past experiences refining the stored knowledge which is re-used in future situations.

An extensive demonstration of the effective, fast and adaptive control to prevent voltage instability in the IEEE 39 bus and 145 bus system is presented and compared. Simulation results show its potential capability of reducing the solution space and making it a scale irrelevant method.

The basic functions and structure of this ACVC is presented in section II. The form of knowledge is the key factor of realizing ACVC. The form of the knowledge and how to save and recover it is presented in section III. The full calculation flowchart of ACVC is introduced in section IV. The simulation results and discussions are in section V. Conclusions are presented in section VI.

II Adaptive Coordinated Voltage Control

There are four main functional blocks (Figure 1) of this adaptive coordinated voltage control (ACVC) system. The accumulated system knowledge together with an on-line search provides for an effective, fast and adaptive system response. Firstly, the search efficiency is improved when the search space is reduced by system knowledge. Secondly, the knowledge is accumulated and optimized by optimal searches.

The form of knowledge representation is thus a key

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feature of this adaptive control system. Firstly, this knowledge should be able to construct a reduced solution space in which only high quality solutions are involved. Secondly, the retrieving of knowledge is programmable to avoid subjective choices. Thirdly, refinement of the knowledge is easily realized so that it can follow the dynamics and changing operation of power systems.

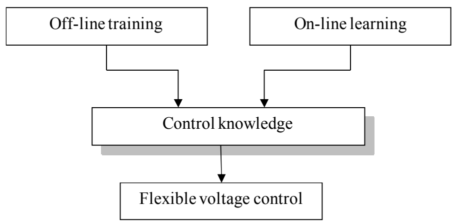


Fig.1 Functional Blocks of Adaptive Voltage Control System

The concept of a Pareto front, providing a set of optimal tradeoff solutions, is adopted for multi-objective OCVC. Once the objectives are properly selected, a set of effective control solutions for voltage control can be obtained from the Pareto solutions. By only searching among those effective solutions, a fast response can be attained. Thus, the Pareto solution set is used as a knowledge base for control solutions.
Based on the form of knowledge, how to prepare, learn and exploit the Pareto solution set are the three main parts to realize this new ACVC strategy:

1. Off-line long-term optimization for anticipated faults

Control knowledge is firstly prepared off-line before ACVC is ready to be applied on-line. Some faults, i.e. tripping of a transmission line or increasing of loads, that may cause voltage instability of a power system are studied. They are called anticipated faults. For each of them, a set of Pareto solutions can be obtained by long-term search. Useful control knowledge can be obtained from these Pareto solutions. It is saved into a database and will be applied to improve the effectiveness of the on-line search.
Meta-heuristic algorithms, well-known for their high standard of global optimization for combinatorial optimization problems, are used to obtain the Pareto solutions. Two types of information are extracted and saved into the database: a) a set of objective values; b) an order of effective control actions which are sequenced according to their efficiencies of recovering bus voltages. (Figure 2)
Possible emergencies considered here are tripping off one element, a generator or a transmission line. Each emergency has its own Pareto solution set which are stored as prepared knowledge.

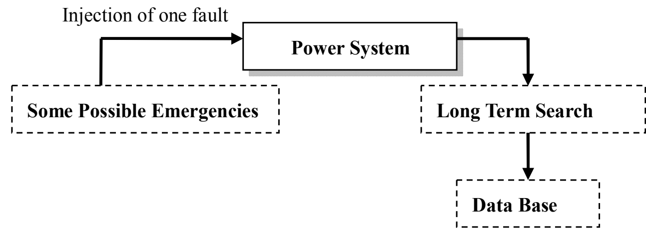


Fig.2 Knowledge Preparation by Off-line Optimal Search

2. On-line adaptive control for prepared faults

To provide an effective feasible solution within a limited time interval, the prepared control knowledge is used to conduct an on-line search. The prepared Pareto solutions are high quality solutions from off-line training and past experiences. They can constitute a reduced solution space in which the search efficiency can be dramatically enhanced, especially for large-scale power systems.
Thus, a fast real time search which concentrates in the Pareto solution area and at the same time combines some of random solutions from the wider solution space can reach an effective control solution.

3. On-line learning for unexpected faults

The on-line control and learning processes are presented in Figure 3.

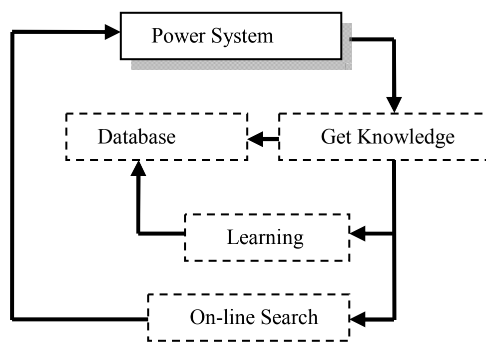


Fig.3 Adaptive Coordinated Voltage Control

A capability of learning is a basic characteristic of intelligent systems. To meet fast dynamic changes of power systems a learning scheme is coupled with ACVC. While the ACVC is applied online, control knowledge is kept accumulated and refined by current experiences. As a result the control performances are improved gradually for future emergencies.
The learning search is also focused in a reduced solution space to improve searching efficiency. An unexpected fault falls into two different situations: i) The first time when the unexpected fault occurs: the control knowledge is acquired from its close faults which are geographically

connected with this new emergency; ii) For the later times when an unexpected fault occurs: the partially fulfilled knowledge from past experiences can be used as a basis for searching. If there is no improvement on the searched Pareto solution set after two runs of the learning process, they are considered as complete knowledge. This fault will no longer be treated as an unexpected fault. In the subsequent times that it happens, it becomes a prepared fault.

III. Multi-objective CVC and System Knowledge

The power system model for CVC is usually mathematically expressed in the hybrid differential-algebraic (DA) form:

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

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

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

where x and y are the dynamic and algebraic state variables while $z(k)$ denotes discrete control variables that can change only at a selected sample time.

Optimal CVC (OCVC) provides optimal scheduling information of voltage controllers within a wide area for maintaining system voltages. For system models with Eq.(1) to (3), OCVC tries to find out optimized $z(k)$, so that the bus voltages represented by y can be maintained within desirable levels. This is a hard combinatorial optimization problem.

The control scheme in this study is based on multi-objective OCVC as multiple solutions obtained from multi-objective optimization may capture more system information and improve the control efficiency. It is thus a multi-objective combinatorial optimization problem.

Two objectives are considered in this study. The objective functions are,

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

$$J_{act} = \min \sum_i m_i \tag{5}$$

where $V_{i,t}$ denotes the voltage of bus i at time t; $V_{i,ref}$ denotes the reference voltage at bus i; m_i is the movement steps of discrete controller i.

For multi-objective optimization, the concept of domination is used to compare the priority of two solutions. Considering 'n' objectives, without loss of generality the minimization is:

$$\text{Min } f_1(x), f_2(x), \cdots, f_n(x) \tag{6}$$

where $f_1(\cdot)$, $f_2(\cdot)$,…, $f_n(\cdot)$ are x objectives to be minimized.

Consider two solutions x and y which have the following relations

$$f_i(y) \le f_i(x) \text{ for } \forall i \text{ and } \exists j : f_j(y) < f_j(x) \tag{7}$$

It is said that solution y dominates solution x . If a solution is not dominated by any other solutions, it is a non-dominated solution. All the possible non-dominated solutions within the solution space constitute a Pareto front.

A solution space with two objectives is represented in the gray area as in Figure 4. A number of solutions are generated randomly in this solution space, namely "P1" to "P4", "N1" to "N3" and "R1" to R6". Solution "N1" dominates solutions "R1", "R4"and "R5" while "N3" dominates "R1" to "R6". Solution "P1" to "P4" are the real Pareto solutions located on the edge of the solution space. If Pareto solutions "P1" to "P4" are not obtained, solution "N1" to "N3" are the available non-dominated solutions.

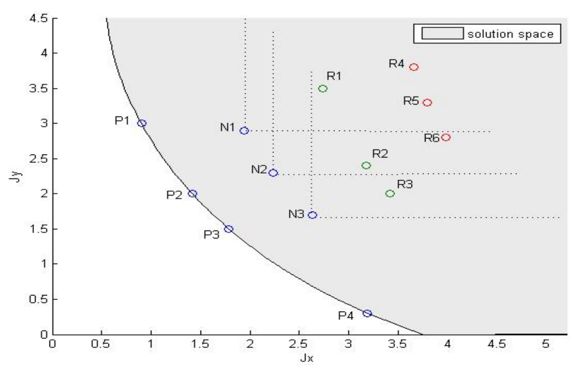


Fig.4 Domination and Pareto solutions

When the solution space is large and high dimensional, the real Pareto front cannot be obtained without an exhaustive search. In most cases, the concept of "non-dominated solution set" is used instead of "Pareto solution set". The non-dominated solutions are preferred and considered as most desirable solutions.

Objectives in Eq.(4) and Eq.(5) are the two objectives being considered for solving the OCVC problem in this paper. The CVC controllers, such as OLTC, capacitor and load shedding, considered in this study are all discrete control variables. J_{act} , given in Eq.(5), counts the moving steps of all controllers and thus $J_{act} \in N^{+}$. So the feasible solutions in the solution space are located in lines with $J_{act} = 1,2,3,4$ as shown in Figure 5.

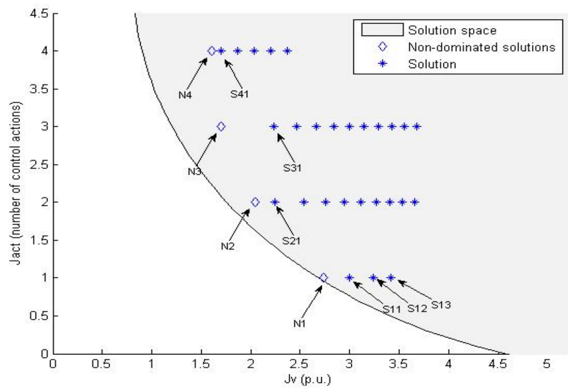


Fig.5 Non-dominated solutions and most effective control

Solution " N_1 " and "S11", "S12", "S13"are feasible solutions with $J_{act} = 1$ which only moves only one step. Among this set of solutions, " N_1 " is the most effective control of increasing bus voltages , as it has the minimum value on objective $J_{\sum vi}$ and hence is the best one to recover bus voltages.

The non-dominated solutions are " N_1 " to " N_4 " as no other solutions can dominate them. Similarly, solution " N_2 " to " N_4 " are the most effective controls of solutions using two to four control actions. Among all current solutions, non-dominated solution set " N_1 " to " N_4 " are the effective solution set. As these non-dominated solutions have these interesting characteristics, they are stored as system knowledge and exploited in following applications.

Based on the form of knowledge, how to save and recover knowledge from the database should be defined.

As each fault has a set of non-dominated solutions, one fault is identified (in Fault Table) and mapped with its knowledge. The knowledge includes two kinds of information of its non-dominated solution set: i) the objectives of the non-dominated solutions stored in the Performance Table ; ii) the corresponding control actions of each non-dominated solution in the Control Table.

After a long-term off-line search or a process of on-line learning, a set of non-dominated solutions can be acquired. The fault is stored as one entry in a "Fault Table" as shown in Figure 6 with its location, type of element and emergencies. Then, all the objectives of each non-dominated solutions are saved in the "Performance Table", while related control actions which correspond to this fault are saved in a "Control Table" .

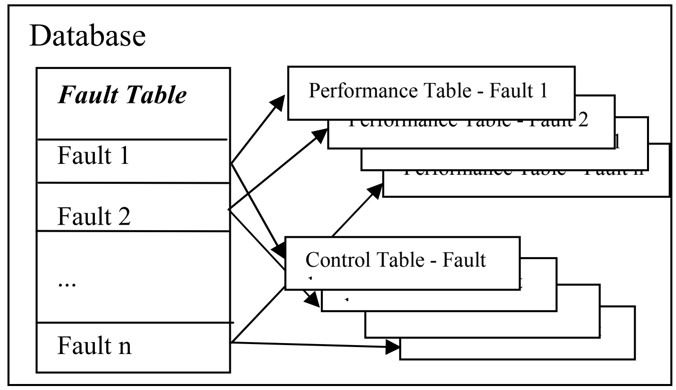


Fig.6 Structure of the database

When a fault is detected, it is firstly identified in the "Fault Table" by its location and the faulty element involved. Once the fault is identified, the related information of non-dominated solutions can be obtained from its "Performance Table" and "Control Table". Based on this knowledge, the on-line adaptive control process is triggered to provide a high quality solution with fast system responses.

IV. On-line Process of ACVC

There are two stages of the ACVC algorithm applied to a disturbed power system. In the first stage, an off-line long term search is used to get a non-dominated solution set for each of the anticipated faults. The objective values and related controls of the non-dominated solutions are stored in the database as prepared system knowledge.

After this off-line preparation, an on-line adaptive control can be realized with the additional learning capability of ACVC. Once an emergency occurs, the computational steps of this on-line adaptive control are as below:

Step 1): Evaluation.

The system's situation is identified according to the predicted system output in the coming control interval. If a collapse occurs before the end of the coming control interval, it is regarded as a short-term situation. Otherwise, it is treated as a long-term situation.

Step 2): Identifying fault.

The fault is compared with the knowledge in the database with its location and type in the "Fault Table":

If it is identified as a "prepared fault" with fully acquired non-dominated solution set, go to step 3);

If no close fault exists, it is identified as an unexpected fault with no past experience, go to step 4);

If the same fault is found and it is identified as unexpected with partially fulfilled knowledge, go to step 5).

Step 3): Getting knowledge for prepared fault.

For a short-term situation, the corresponding objective values in the Performance Table are obtained after the fault is identified in the database. If it is a long-term situation, a full order of controls of non-dominated solutions is obtained from the Control Table. Based on the control knowledge, the objectives are calculated with current system conditions. Newly obtained objective values of each controls are stored in the database to update system knowledge. Go to Step 6).

Step 4) Finding close faults for unexpected fault with no past knowledge:

According to its location, the neighboring faults are selected as follows:

a) If the new fault is the tripping of an element, the neighboring faults are the tripping of the corresponding generator and transmission lines connected to the bus.

b) If it includes more than one element, each one is considered separately. The neighboring faults are taken as a combination of all for the faults. If any one of these elements is a prepared fault, the knowledge of this prepared fault is gathered to form the knowledge pool.

If it is identified as a short-term situation, all the control actions in the knowledge pool are applied to the system with no delay. Then, end the program. For a long-term situation, The control actions in the knowledge pool form a reduced solutions space. An on-line search is then used to find non-dominated solutions in this reduced solution space. It may not be able to find an adequate non-dominated solution set within such a short control interval. Then the searched non-dominated solutions are called pseudo-knowledge and stored in the database. This unexpected fault is then marked as unexpected with partially fulfilled knowledge. Go to Step 6).

Step 5): Getting knowledge for unexpected fault with past knowledge:

The pseudo-knowledge which is learnt in past experiences are selected from the database. All controls of non-dominated solutions are combined to form a pool. If it is a short-term situation, the solution with the least value of $J_{\sum v}$ is selected from the "Performance Table". Its corresponding control in the "Control Table" is then applied to the power system. End the program.

If it is identified as a long-term situation, a random on-line search is used to get an improved non-dominated solution set. The solutions from the pseudo-knowledge are used to generate part of the initial population for the search. The rest of the initial population is generated randomly within the solution space to keep diversity.

Newly obtained non-dominated solutions are compared with stored pseudo-knowledge; if there are no improvements, the acquired non-dominated solutions are taken as the complete control knowledge which is saved in the database. It will be considered a prepared fault the next time it occurs. If there are improvements, the newly acquired knowledge is stored to update system knowledge.

Go to step 6).

Step 6) selecting best solution.

For real time control, the selection consideration would be judged with respect to the state of the power control system. The multiple criteria decision making (MCDM) technique can be applied to make selection from the non-dominated solution set. The proposed scheme is based on Multi-Attribute Utility Theory (MAUT) [8] which is the more widely applied multiple criteria method.

The preferences which are reflected by the weights of the objectives can be set in advance or changed on-line. The objective values are used to get the scores of each solution by MCDM analysis [9]. The one with the highest score becomes the best solution for the specified preference. The best solution is then applied as a control solution.

Step 7): Saving knowledge. Waiting for a next emergency. End program.

V. Simulation Results and Discussion

The ACVC control strategy is tested with two IEEE standard systems. There are two faults in a sequence considered for each system. The ACVC is used to get emergency voltage control for fast recovery of the bus voltages. It is of interest to study to what extent the ACVC approach can help overcome the problem of dimensionality as the size of the system grows.

Prepared faults are assumed to be tripping of a generator or tripping of a transmission line. Off-line long term search is applied to get a non-dominated solution set for each of these prepared faults. Prepared knowledge is then stored in the database as explained above. While ACVC is applied on-line, system knowledge is kept being refined according to real time system structures and operational situations. For any new fault, the learning process is trigged to accumulate new knowledge during operation.

The control interval is set as a fixed time span of 30s while a detection time is also set as 30s. The control devices begin to react at the instance of 60s with an activation time of 30s. Hence, the control actions may take place at the sequence of 60s, 90s, 120s and so on. If a fault happens at time t and 30s is needed for fault detection, the controls are started from t +30s.

Case study 1: IEEE 39 bus system

There are 12 on-load tap changers (OLTCs), 19 load shedding sites and 17 capacitors acting as voltage controllers in the IEEE 39 bus system. Detailed parameters of this power system can be found in [4,9].
The testing scenario is listed in Table 1. System performance is given in Figure 7. It can be seen that after a sequence of events, the system can be kept within desirable values.
ACVC provides emergency control for two emergencies. For the first fault, it takes 7 control intervals to recover system voltages. The second fault is not as serious as the first one. Only two control intervals is enough to recover system voltages.

Table.1 Testing scenario of IEEE 39 bus system

Time	Event
30 s	Line 3-2 tripping
60 s	ACVC start
180 s	Line 3-2 reconnection
450 s	Generator 36 tripping
480 s	ACVC start
600 s	Generator 36 reconnection

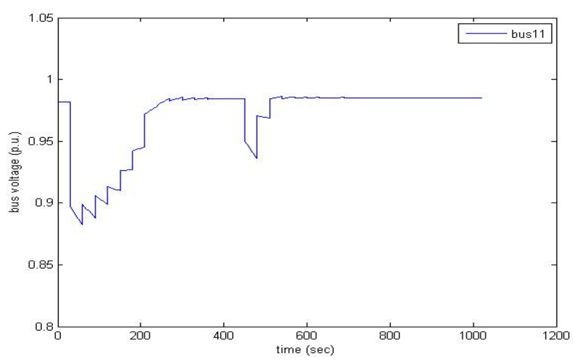


Fig.7 System performance of ACVC for IEEE 39 bus system

Case study 2: IEEE 145 bus system

IEEE 145 bus system has 52 on-load tap changers (OLTCs), 64 load shedding sites and 97 capacitors. The number of voltage controllers is far greater than that of the above 39 bus system. Accordingly, the full solution space which are defined by the number of controllers and their available movement steps is increased greatly.
The testing scenario is listed in Table.2. The controlled system performance is given in Figure 8. The fault of tripping Line 76-77 is more serious than the fault of tripping generator 100. It takes 4 control intervals for the first fault, while only 2 control intervals for the second fault.

Table.2 Testing scenario of IEEE 145 bus system

Time	Event
30 s	Line 76-77 tripping
60 s	ACVC start
180 s	Line 76-77 reconnection
450 s	Generator 100 tripping
480 s	ACVC start
600s	Generator 100 reconnection

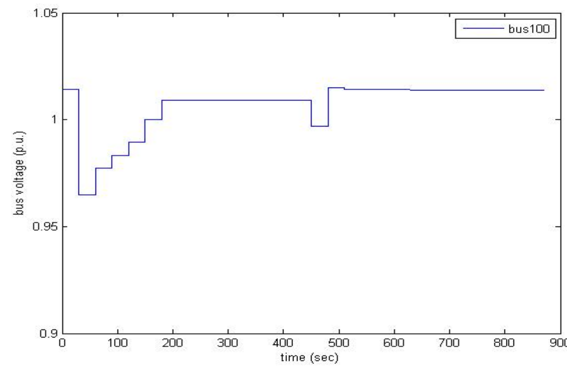


Fig.8 System performance of ACVC for IEEE 145 bus system

Comparisons and Discussions:

1) For the knowledge preparation, any modern heuristic search technique can be used. With a random global search, a large population in the solution space should be visited to get a high quality non-dominated solution set. A population of 100 with a maximum generation of 100 is applied for each run of the optimal search by genetic algorithm. This may take more than 6 minutes. The non-dominated solution set is obtained after 10 runs.
2) The population of the on-line search is set as 10 and maximum generation is 10. There are totally 100 solutions from the knowledge base which can be visited for each prepared fault. According to our study, the number of non-dominated solutions of all prepared faults is not exceeding 100. So in the worst cases, it takes no more than 4 seconds to finish an on-line adaptive search for a prepared fault.
3) For on-line learning, a population of 30 and number of generation of 30 is applied. It takes about 28 seconds for a learning process. This is less than 30 seconds which is set as the control interval. In the next control interval, learnt knowledge can be exploited for new situations.
4) For the same system, the number of non-dominated solutions are related to the seriousness of the emergencies. The objective of $J_{\sum vi}$ can indicate the seriousness of a fault. The bus voltage deviation of every buses in a power system are summed together. The larger

the bus voltage deviations, the more non-dominated solutions can be found. (Table.3)

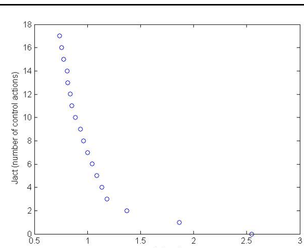
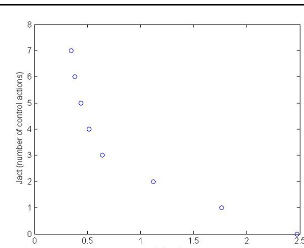
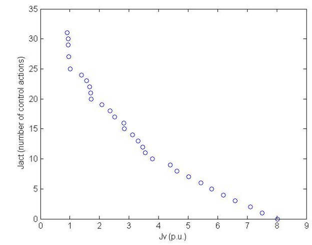
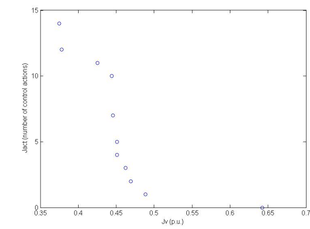
5) The seriousness of a fault for the two power systems can not be compared with this objective of $J_{\sum vi}$ as they are summed with different number of buses. We attempt to represent the seriousness of a fault with "Most serious bus voltage deviation". This may indicate the seriousness in some extent as the instability of one bus may cause a blackout of the whole system. From the results listed in Table 3, we can find that the number of non-dominated solutions are not increased with the scale of the systems.

6) Searched non-dominated solutions sets of each fault are presented in Table.4. The knowledge base is formed with the objective values of these solutions. They are exploited and refined by the on-line search.

Table.3 Result Comparisons

Systems	Faults	Most serious bus voltage deviation	objective of $J_{\sum vi}$	Number of non-dominated solutions
IEEE 39 bus	Tripping Line 3-2	0.0432p.u.	0.5459 p.u.	18
	Tripping Generator 36	0.0585p.u.	2.4725 p.u.	8
IEEE 145 bus	Tripping Line 76-77	0.1522p.u.	8.0170 p.u.	30
	Tripping Generator 100	0.0492p.u.	0.6422 p.u.	11

Table.4 Non-dominated solutions of fault

Systems	Faults	Non-dominated solutions
IEEE 39 bus	Tripping Line 3-2	
	Tripping Generator 36	
IEEE 145 bus	Tripping Line 76-77	
	Tripping Generator 100	

VI. Conclusions

A new adaptive coordinated voltage control strategy is proposed in this paper. Based on the system knowledge prepared off-line by long-term optimal search and refined on-line by learning processes, an on-line search within a reduced solution space can provide voltage control in an efficient manner.

According to system simulation on two test systems, this adaptive voltage control can provide a very fast and effective solution to prevent voltage instability in the presence of multiple contingencies. At the same time, dramatic changes of dynamics of a power system can also be handled and system performances maintained.

Further work intends to explore the issue of system dimensionality and how it relates to computational demands for ACVC. Control across the transmission, sub-transmission and distribution layers raises new challenges in dimensionality.

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