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Bayesian Networks Design of Load-Frequency Control based on GA

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***Abstract*—Frequency regulation in interconnected networks is one of the main challenges in power systems. Significant interconnection frequency deviations can cause under/over frequency relaying and disconnect some loads and generations. Under unfavorable conditions, this may result in a cascading failure and system collapse. A control strategy for solving this problem in a multi-area power system is presented by an intelligent based load frequency control (LFC) using Bayesian networks (BNs). This method admits considerable flexibility in defining the control objectives specifically in a large scale power system. The BNs provide efficient probabilistic inference algorithms that permit answering various probabilistic queries about the system and incorporate expert knowledge and historical data for revising the prior belief in the light of new evidence in many fields. It is also possible to include local conditional dependencies into the model, by directly specifying the causes that influence a given effect.**

To demonstrate the capability of the proposed control structure, a three-control area power system simulation with two different scenarios is presented.

***Index Terms*— Bayesian Networks; Load-frequency control; genetic algorithm**

I. Introduction

THE load-frequency control (LFC) is known as one of the important power system control problems in multi-area power systems [1, 2]. Since, the classic and linear control methodologies are usually suitable for specific operating points, if the dynamic/structure of system varies; they may not perform as expected for the LFC loop design in a power system. Most of conventional control strategies provide model based controllers that are highly dependent to the specific models, and are not usable for large-scale power systems with nonlinearities, undefined parameters and uncertain parameters. Also if the dimensions of power system increase, these control design may become more difficult as the number of the state variables increase, significantly.

Therefore, design of intelligent controllers that are more adaptive and flexible than conventional controllers is become an appealing approach. Intelligent controllers has been widely used for the frequency regulation issue in the power systems [3-5]; however there are just few reports on using Bayesian Networks on the frequency control design [6, 7].

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Bayesian Network (BN) is one of the adaptive and nonlinear control techniques that can be applicable in the LFC design. BNs are powerful tools for knowledge representation and inference under conditions of uncertainty. They have been successfully applied in a variety of real-world engineering tasks but they have received little attention in the area of power system control issues. It has been effectively used to incorporate expert knowledge and historical data for revising the prior belief in the light of new evidence in many fields. The main feature of the BN is that it is possible to include local conditional dependencies into the model, by directly specifying the causes that influence a given effect [8].

Since, the BNs are based on learning methods then they are independent of environment conditions and can consider all kinds of environment disturbances, so they are not model based and can easily scalable for large scale systems, such as power systems. They can also work well in nonlinear conditions and nonlinear systems.

This paper addresses the LFC design using an intelligent solution for a large interconnected power system. Here, a Bayesian Networks control structure is proposed. It has one controller in each control area that provides an appropriate control signal according to load disturbances and tie-line power changes received from other areas.

The above technique has been applied to the LFC problem in a three-control area power system as a case study.

The organization of the rest of the paper is as follows. In Section 2, a brief introduction to LFC problem and BN is given. In Section 3, the proposed intelligent frequency control technique using BN and the structure of a network which the above architecture is implemented for are discussed. It is also explained that how a load-frequency controller and the test cases study can be work within this formulation. Simulation results are provided in Section 4 and the paper is concluded in Section 5.

II. Preliminaries

A. LFC Model

As mentioned, a three-control area power system used to examine the applicability of the proposed intelligent controller. The block diagram of a control area-i of the test system which includes n Gencos, is shown in Fig. 1[9].

Within a control area, following a load disturbance, the frequency of that area experiences a transient change, the feedback mechanism comes into play and generates appropriate rise/lower signal to the participating Gencos

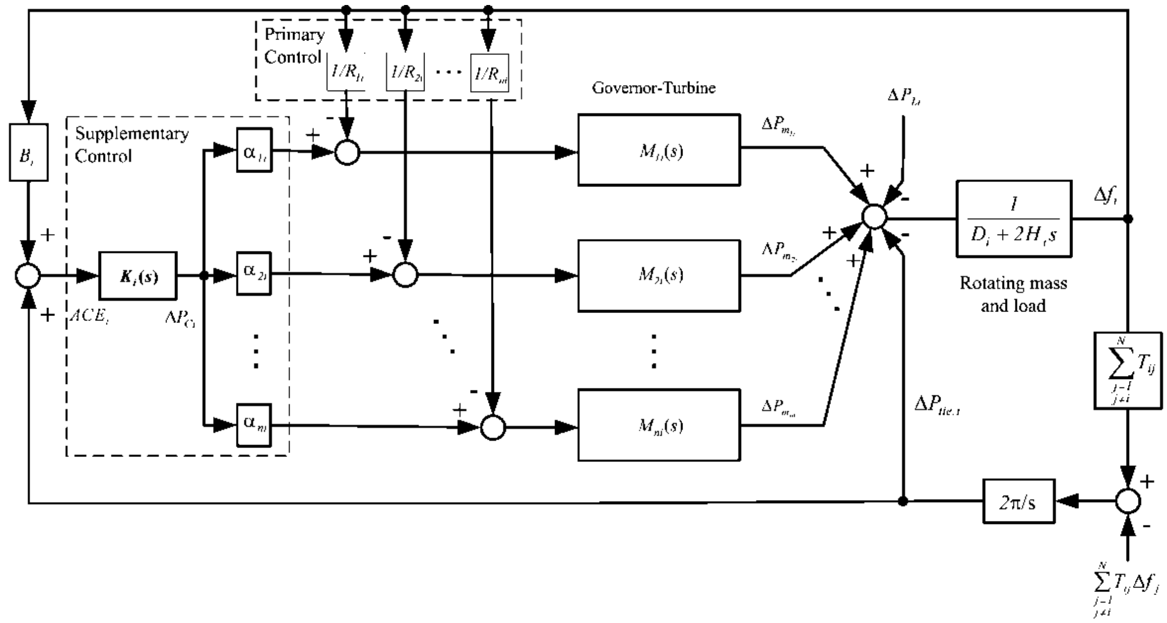


Fig. 1 LFC system with different generation units and participation factors in area i [9]

according to their participation factors (α_{ji}) to make generation follow the load. In the steady state, the generation is matched with the load, driving the tie-line power and frequency deviations to zero. Therefore the *ACE* for each control area can be expressed as a linear combination of tie-line power change and frequency deviation (according to (1)) [9].

$$ACE_i = \beta_i \Delta f_i + \Delta P_{tie-i} \tag{1}$$

B. Bayesian Networks

In real learning problems, there is large number of variables with relationships. The BN is a representation suited to this task. It includes a graphical model that efficiently encodes the joint probability distribution for a large set of variables.

A probabilistic graphical model is a mathematical graph in that nodes are random variables, and arcs represent conditional independence assumptions between variables [10]. If there is no arc between two nodes, they are independent nodes else they are dependent variables. The arcs pattern provides a concise representation of joint probability distributions. In a graphical model an arc from node A to B can be informally interpreted that A "causes" B, (Which A is the parent node of B and B is the child node of A) [10].

In summary a BN consists of three components *(i)* a graphical model S, *(ii)* a set of random variables $x=\{x_1,\ldots,x_n\}$ (the graph nodes) and a set of arcs that determines the nodes (random variables) dependencies, and *(iii)* a conditional probability table (CPT) associated with each variable ($p(x_i|pa_i)$).

Together these components define the joint probability distribution for x. The nodes in S are in one-to-one correspondence with the variables x. In this structure, x_i denotes both the variables and its corresponding node, and pa_i to denote the parents of node x_i in S as well as the variables corresponding to those parents. The lack of possible arcs in S encodes conditional indecencies. In particular given structure S, the joint probability distribution for x is given by,

$$p(x_1,\cdots,x_n) = \prod_{i=1}^{n} p(x_i|pa_i) \tag{2}$$

The basic tasks related to the BNs are *(i)* structure learning phase: finding the graphical model structure, *(ii)* parameter learning phase: finding nodes probability distribution, and *(iii)* Bayesian Network inference. The structure and parameter learning are based on the prior knowledge and prior data (training data) of the model.

The basic inference task of a BN consists of computing the posterior probability distribution on a set of query variables q, given the observation of another set of variables e called the evidence (i.e. $p(q|e)$). Different classes of algorithms have been developed that compute the marginal posterior probability $p(x|e)$ for each variable x, given the evidence e.

III. Bayesian Networks Based Controller Design

In this section, an intelligent control design algorithm using BNs technique for a PI controller is presented. The objective of the proposed design is to regulate the frequency in power system with various load disturbances and achieve a desirable control performance.

Fig. 2 shows the proposed model for area i. An intelligent controller is used in this area, which is responsible to provide an appropriate supplementary control action.

A. BN Controller Structure

To illustrate the process of a BN construction, we must (*i*) correctly identify the goal of modeling, (*ii*) identify many possible observations that may be relevant to the problem, (*iii*) determine what subset of those observations is worthwhile to model, and (*iv*) organize the observations into variables having mutually exclusive and collectively exhaustive states.

Here the aim is to achieve the conventional LFC objective and keep the *ACE* signal within a small band around zero using the supplementary control action signal (Fig. 1). Then, the query variable in the posterior probability distribution is ΔP_c signal and the posterior probabilities according to possible observations relevant to the problem are as follows,

$$
\begin{aligned}
& p(\Delta P_c | ACE, \Delta P_{tie}, \Delta P_L, \Delta f) \\
& p(\Delta P_c | ACE, \Delta P_L, \Delta f) \\
& p(\Delta P_c | \Delta P_{tie}, \Delta P_L, \Delta f) \\
& p(\Delta P_c | ACE, \Delta P_{tie}, \Delta P_L) \\
& p(\Delta P_c | ACE, \Delta f) \\
& p(\Delta P_c | \Delta P_{tie}, \Delta P_L) \\
& \vdots \\
& p(\Delta P_c | \Delta P_{tie}) \\
& p(\Delta P_c | \Delta P_L)
\end{aligned}
\tag{3}
$$

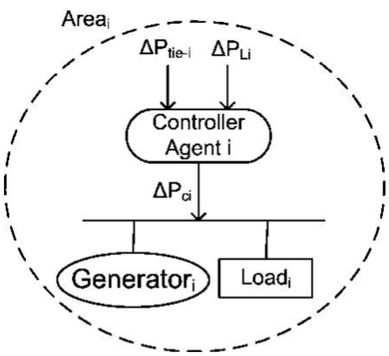


Fig. 2 The proposed model for area *i*

According to (3), there are so many observations that are related to this problem, however the best one that has the least dependency to the model parameters and causes the maximum effect on the frequency deviation and consequently *ACE* signal changes, are load disturbance and tie-line power deviation signals. Then the appropriate posterior probability that should be found is $p(\Delta P_c|\Delta P_{tie}, \Delta P_L)$.

The ΔP_{tie} can be practically obtained. However, the ΔP_L is one of the input parameters that is not measurable directly, but it can be easily estimated using a numerical/analytical method [9]. This estimation method is initially based on the measured frequency gradient and the specified system characteristics [9]. On the other hand, regarding the LFC duty cycle, the total consumed time needed for the estimation process is not important.

After determining the most worthwhile subset of the observations (ΔP_{tie}, ΔP_L), in the next phase of the BN construction, a directed acyclic graph that encodes assertion of conditional independence is built. It includes the problem random variables, nodes conditional probability distribution and nodes dependencies (Fig. 3).

B. BN Learning and Inference

As mentioned and is shown in the graphical model of a control area (Fig. 3), the essential parameters used for the learning phase among each control area of the test system are considered as ΔP_{tie}, ΔP_L, and ΔP_c.

In this step of BN construction (parameter learning), the local conditional probability distribution(s) $p(x_i|pa_i)$ are computed from the training data. Probability distributions and conditional probability distribution related to this problem according to Fig. 3 are: $p(\Delta P_L)$, $p(\Delta P_{tie})$ and $p(\Delta P_c|\Delta P_L,\Delta P_{tie})$.

After providing the training set, the training data related to each area are separately given to the Bayesian Network Toolbox (BNT) (11). The BNT uses the input data and do the parameter learning phase for each control area parameters. It founds prior and conditional probability distribution related to that area's parameters, which according to Fig. 3, are $p(\Delta P_L)$, $p(\Delta P_{tie})$ and $p(\Delta P_c|\Delta P_L,\Delta P_{tie})$.

Once, a BN has been constructed (from prior knowledge, data or a combination), various probabilities of interest from the model are determined. For the problem at hand, it is desired to compute the posterior probability distribution on a set of query variables, given the observation of another set of variables called the evidence. The posterior probability that should be found is $p(\Delta P_c|\Delta P_{tie},\Delta P_L)$. This probability is not stored directly in the model, and hence needs to be computed. In general, the computation of a probability of interest given a model is known as *probabilistic inference*.

During the simulation stage and after the learning phase completed, the probabilistic inference phase is done as follows: at each simulation time step, corresponding controller of each area gets the input parameters (ΔP_{tie}, ΔP_L) of the model, and digitizes them for the BNT (the BNT does not work with continuous values). The BNT finds the posterior probability distribution values $p(\Delta P_c|\Delta P_{tie}, \Delta P_L)$ related to each area (see Table I). Then, the controller finds the maximum posterior probability distribution from the return set, and gives the most probable evidence ΔP_c in the control area. Using this change to the governors setting, the current values of the load disturbances and the tie-line power deviation are integrated for the next time.

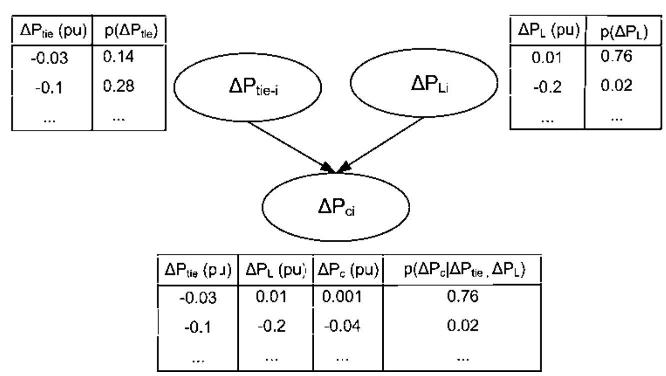


Fig. 3 The graphical model for area *i* [7]

Table I
Returned Posterior Probability Distribution Values From BNT of Area $i=2$ for $\Delta P_{tie-i,}=0.03$ and $\Delta P_{Li}=0.01$

$p(\Delta P_{ci}|\Delta P_{tie-i},\Delta P_{Li})$	0.005	0.1	0.032	0
$\Delta P_{ci}\,(pu)$	-0.08	0.03	0.1	-0.005

C. Finding Training Data based on GA

Here genetic algorithm is used to find a related set of training data (ΔP_{tie}, ΔP_L, ΔP_c) and to gain better results. It produces a ΔP_c vector and the simulation is run (with the obtained ΔP_c) for a special load disturbance. Then the appropriate ΔP_c is evaluated based on the gained *ACE* signal.

The start population size is equal to 30 individuals and it was run for 100 generations.

To find individual's eligibility (fitness), after finding the corresponding ΔP_c, the simulation is run for a special ΔP_L (a signal with 100 instances) and with above ΔP_c, for 100 seconds. The individual's fitness is proportional to the average distances of gained ACE signal instances from zero after 100 seconds simulation. Each individual that causes to smaller fitness is the best one and the tuple (ΔP_{tie},ΔP_L,ΔP_c) related to that simulation is one row of the training data matrix [7].

IV. Simulation Results

To demonstrate the effectiveness of the proposed control design, some simulations are carried out. In these simulations, the proposed controllers are applied to the three-control area power system model described in Section II and III (see Fig. 4), and will be tested for the various possible load disturbances. It is assumed that each control area includes three Gencos and its parameters are given in [9].

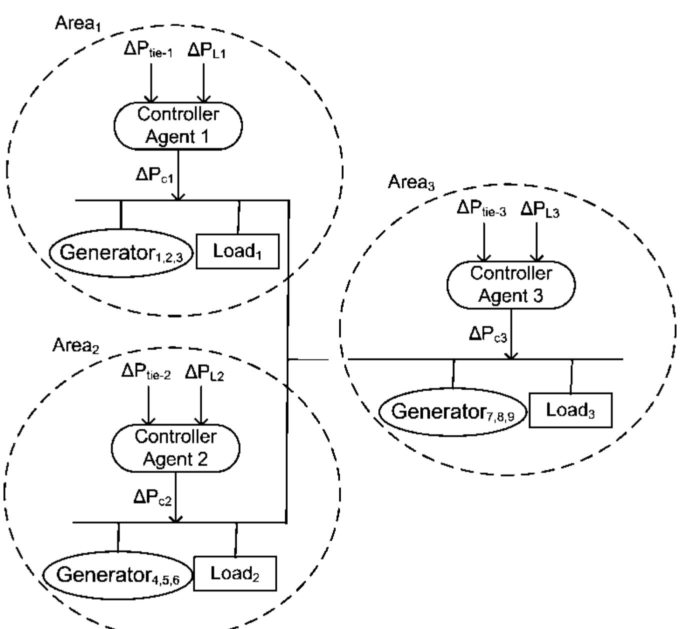


Fig. 4 The proposed model for the three-control area

Scenario 1: As the first test case, the following large load disturbances (step increase in demand) are applied to three areas:

ΔPd_1=100MW; ΔPd_2=80MW; ΔPd_3=50MW;

The frequency deviation (Δf) area control error (*ACE*) and control action (ΔP_c) signals of the closed-loop system are shown in "Fig. 5".

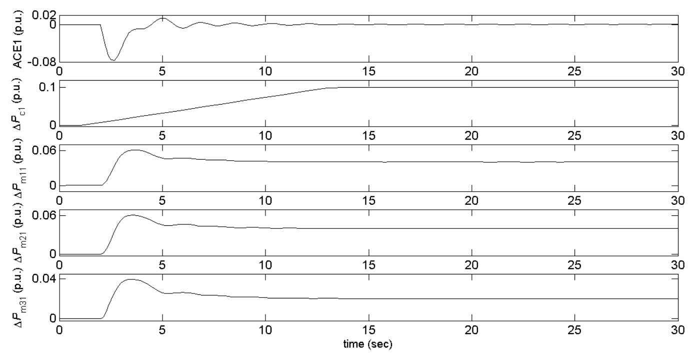
Scenario 2: Consider larger demands by areas 2 and 3, i.e.

ΔPd_1=100MW; ΔPd_2=100MW; ΔPd_3=100MW;

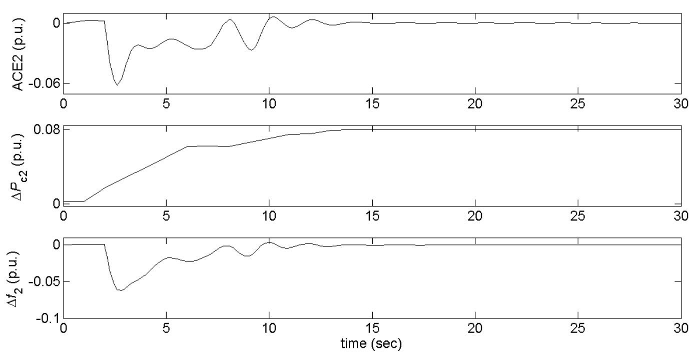
The closed-loop responses for each control area are shown in "Fig. 6".

The simulation results for the test system illustrate the capability of the proposed intelligent based LFC scheme. As it is obtained from the above pictures the proposed method causes the ACE and frequency deviation of all areas are properly driven back to zero, the convergence speed of the frequency deviation and the ACE signal to its final values are good, also the generation control signal deviation (ΔP_c) change is low and it smoothly goes to the steady state and satisfies the system physical conditions well.

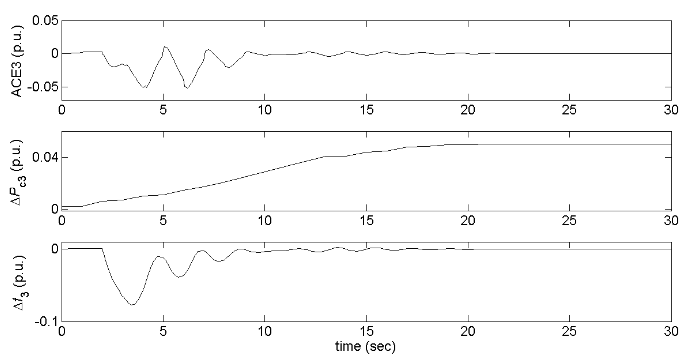
In summary, flexibility, higher degree of intelligence, model independency, and handling of incomplete measured data (uncertainty consideration) can be considered as some important advantages of the proposed methodology.



(a)

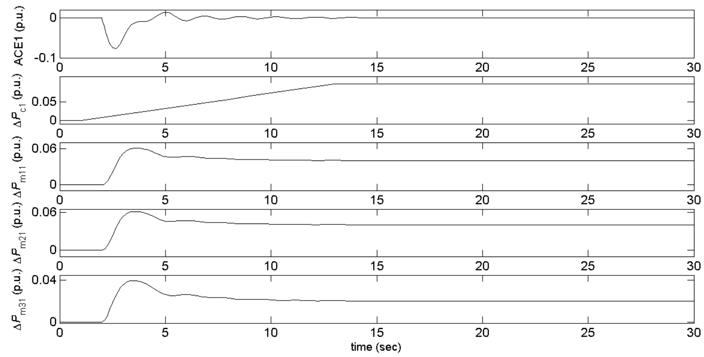


(b)

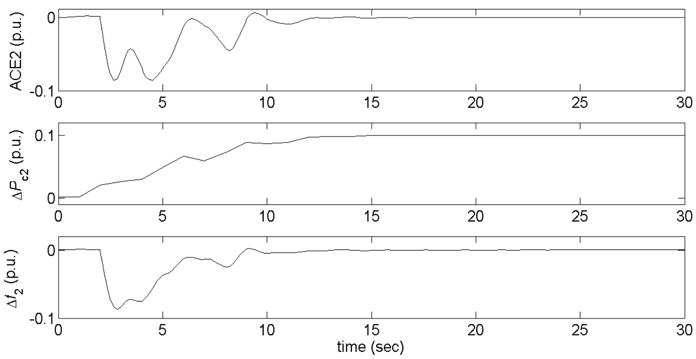


(c)

Fig. 5: System responses in case 1, (a) area 1, (b) area 2, (c) area 3



(a)



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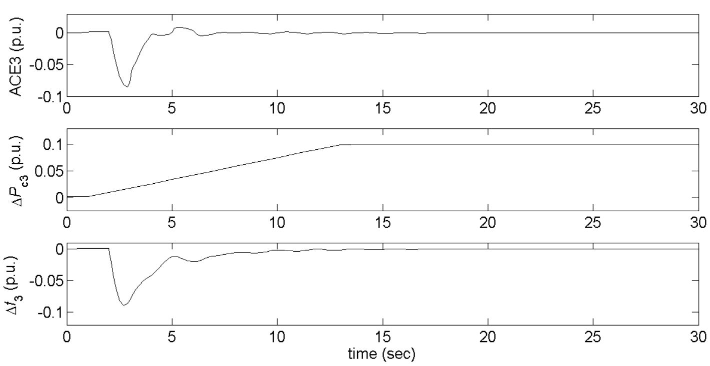

(c)

Fig. 6: System responses in case 2, (a) area 1, (b) area 2, (c) area 3

V. CONCLUSION

A new method for frequency regulation using a Bayesian networks has been proposed for a three-control area power system. The results show that the new algorithm presents a desirable performance. Two important features of the new approach, i.e. model independence from power system parameters and flexibility in specifying the control objectives, make it very attractive for frequency control practices.

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