THE NEURAL NETWORK MODELING APPROACH FOR LONG RANGE EXPANSION POLICY OF POWER PLANT CENTERS

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Abstract Traditionally, Electrical power plant capacities are determined after specific plant locations have been selected. In this paper an expansion policy of power plant centers involving the choice of regions that must be allocated to power plant centers and power plant centers capacities over a specified planning horizon (years) is tackled. The problem is performed as a mixed integer-programming model and solved using a modified Hop field's neural network model designed for (T.S.P) travel salesman problem. This paper makes an approach to estimate number of centers, optimum distributions power respect to minimizing fixed investment and operational cost in long term.

Key Words Neural Network, Mathematical Modeling, Power Plant

چكيده معمولا ظرفيت مراكز توليد نيرو (نيروگاهها) پس از تعيين محل استقرار آنها انجام مي‌گيرد. در اين مقاله سياستهاي توسعه مراكز توليد نيرو با توجه به نوع منطقه و ظرفيت مورد نياز با نگرشي خاص انجام مي‌گيرد. مدل سازي به كمک برنامه ريزي رياضي توسعه پيدا كرده و سپس با توجه به مفهوم شبكه هاي عصبي هوپ فيلد بهينه تعداد نيروگاههاي مورد نياز محاسبه مي‌گردد. راهيافت مدل توسعه داده شده مي‌تواند به تعيين نوع مراكز، محلها و نحوه توزيع اين مراكز با هدف حداقل كردن هزينه هاي سرمايه گذاري و عمليات در بلند مدت منجر گردد.

INTRODUCTION

Economic development in any region of the world is closely related to availability of energy. This is more so in industrial areas of developing countries, in some of these countries, regions are sometimes rapidly and indiscriminately connected to electricity power plant network with out considering the economic viability and availability of generation and distribution capacity in long term. The major problem inherent in expansion policy of power plant centers is high investment that makes their optimal design very crucial for economically viable application in long term. Expansion policy of power plant centers has been discussed in numerous publications. Most of the existing literatures consider policy for one time period (year) and one load center. However, The problem often faced by people responsible for planning of energy development in how to increase generation capacity in a specific time frame extending over one time period while attaining certain objectives. The objectives are typically lower investment and operation costs. The Problem of choosing the capacities of power plant centers over a period of time is known as an "expansion policy problem".

Many researchers have studied this problem by using mathematical methods, such as linear programming [1,2,3] and dynamic programming [4,5,6,7,8,9]. The expansion policy problem generally exhibits a structure that makes decomposition into stages, particularly attractive. This makes dynamic programming or mixed integer programming (DP/MIP) very appropriate when used in conjunction with other optimization techniques like design analysis [7,9], production [8], probabilistic simulation [5,6] and expert system [4,10]. In most cases DP/MIP is employed in last stages of

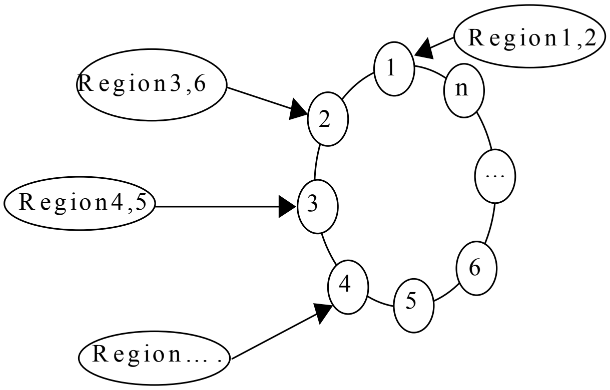


Figure 1. Power plant distribution network.

planning after trail solutions to the expansion policy problem have been generated. One condition of using DP/MIP is that the power plant sizes are known in prior, a requirement that makes DP/MIP unsuitable. In this paper, a neural network approach was used to solve the multi-location (centers) expansion center problem. A model and an algorithm were developed to find the best combination of center location, center size over a number of years and power distribution. The problem was formulated as a mixed integer programming and a neural network method designed for T.S.P (Travel Salesman Problem). Due to the special structure of the problem and model, the well-developed modified network approach was quite successful in obtaining optimal solutions.

PROBLEM DESCRIPTION

An illustration of power plant /distribution network system is shown in Figure 1. It consists of a few power plant centers located in **C** different centers and many regions are fed. Each region is connected to the nearest power plant center in specific period. The produced power energy O_i and demand of power energy of region I in period T is $L_{it.}$ If this is more than the load demand in the region, the excess energy is injected into the other centers. On the other hand, drawing power from the other centers with surplus production rectifies any shortfall in energy supply from one center.

The expansion policy problem discussed in this paper can be stated as follows given:

- Expected load demand data of each region in each period.
- Cost of investment and operational power.

Determine the size of center and grouping regions to be introduced each year over **T** periods to minimize the cost of providing power to the **R** chosen regions while satisfying operational and economic constraints.

SYSTEM MODELING

Hop field's (1982) introduced a network architecture known as the Hhopfields network. His network has a single layer of neuron, and each neuron has a state that can be binary (0,1) or bipolar (-1,1). In this paper binary state will be used. The entire network also has a state at any point in time represented by the state of a vector of neurons. The neurons are fully interconnected and every pair of neurons has connection in both directions. Figure 2 shows a diagram of Hhopfield network. Because of this interconnection topology, output of each neuron feeds into every other neurons and causes the network to be recursive. This recursive feature will allow the network to maintain a stable state. If no external input exists, each interconnection has an associated weight. In the Hhopfield network the connection weights of every pair of neurons have equal value in both directions, (i.e., $W_{XtRt,YtQt}=W_{YtQt,XtRt}$) and there is no self-loop connection (i.e., $W_{XtRt,\ XtRT}=0$). The connection weights have to be set prior to every application and maintain unchanged during updating procedure. These weight values are set in such a

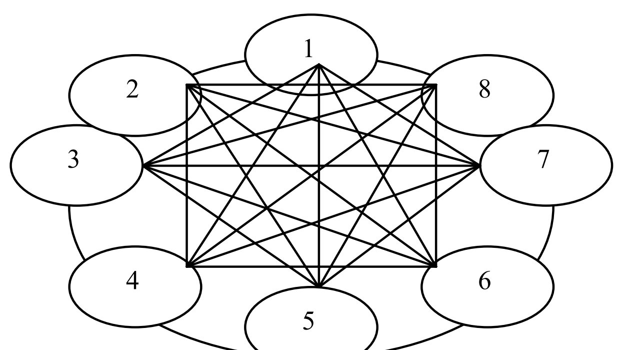


Figure 2. The diagram of hop field's network.

way that the energy function of the network is minimized.

Before starting the updating procedure, an initial value has to be assigned to each neuron. Then one neuron at a time is updated and its output affects the state of other neurons. The updating candidate can be selected either randomly or sequentially. This updating process continues until the network stabilizes at a local or global minimum. The effect of each neuron on every other neuron is influenced by connection weight between them. Let $U_{Xt,\ Rt}$ denotes the state of neuron X_t (i.e. 0 or 1). This value will be the output of neuron X_tR_t to every another neuron, which is a candidate for updating. If neuron Y_tQ_t is an updating candidate, it will be affected by all other neurons according to following equations.

$$\Gamma_{YtQt} = \sum^{M} \sum^{M} U_{XtRt} \cdot W_{XtRt,YtQt}$$
$$\forall\ Y_t, Q_t, X_t Rt \# Y_t Q_t$$

The state of neuron will be updated as follows:

$$U_{YtQt} = \{ 1 \text{ if } \Gamma_{YtQt} >= 0 \text{ AND } 0 \text{ otherwise} \}$$
$$\forall\ Y_t Q_t$$

The energy function in this neural network is

$$E = \frac{1}{2} \sum^{c}\sum^{c}\sum^{c}\sum^{c} W_{XtRt,YtQt} \cdot U_{XtRt} \cdot U_{YtQt}\ (X_t R_t \# Y_t Q_t)$$

Figure 3 illustrates the updating process in the Hhopfield network. This process repeats until a stable state is attained. Base on this network topology, Hhopfield and Tank (1985) proposed a model to solve the traveling salesman problem (T.S.P). In their model, neuron $X_t R_t$, if the salesman visits city X_t in $R^{th}{}_t$ position of the tour, and not active otherwise (t is period that here assumed equal one).

The energy function was selected in such a way that the energy level becomes lower after state changes. The progressive updating of Hhopfield network leads the network to a stable state at which the energy reaches a minimum. This minimum could be either local or global .The following energy function was used in their network:

$$E = \frac{1}{2} A\sum_{xt} \sum_{rt} \sum_{qt} U_{XtRt}\, U_{YtQt} + \frac{1}{2} B \sum_{rt}\sum_{xt}\sum_{yt} U_{XtRt}\, U_{YtRt} + \frac{1}{2}C \sum_{xt}\sum_{rt}(U_{xtrt}-M)^2 + \frac{1}{2}D \sum_{xt}\sum_{yt}\sum_{rt}\sum_{XtYt} U_{XtRt}(U_{Yt,(r-1)t}+U_{Yt,(r-1)t})$$
$$r \# q \quad x \# y \quad yt \# xt$$

The first term of energy function corresponds to the constraint that each city should be visited only once. When this constraint is satisfied, this term has the minimum value. The second term is associated with the restriction that the salesman can visit only one city at a time, i.e. no more than one city can be placed in the same position in the tour sequence. This term will be zero when each city is placed in only one position. The third term will force the number of visited cities to be equal to the M, i.e., all cities should be visited, therefore all the constraint in T.S.P have been incorporated in to the energy function. The objective function of T.S.P minimize total travel distance is reflected by the last term. It is important to note that, unlike most neural networks, Hopfield network does not need the training phase. Therefore, once the connection weights are set, they remain unchanged through out the entire iterative process. The logic represented by the energy function is further mapped to the connection weights used in updating process. The connection weights suggested by Hopfield (1985) have the following form.

$$W_{XtRt,YtQt} = -A\ \delta_{XtYt}\ (1-\delta_{RtQt}) - B\ \delta_{RtQt}\ (1-\delta_{XtYt}) - C - D\ \delta_{XtYt}\ (\delta_{Qt(r+1)t} + \delta_{Qt(r-1)t})$$

$$\forall\ X_t, Y_t, R_r, Q_t$$

The first and second terms in the above weight equation are related to the constraints of the model (i.e., city can not be placed in more than one position in the tour, and one position can not be used for more than one city). They cause inhibitory connection within each row and each column. As A and B have the same effects but in different directions. In most cases A is set equal to B. The third term has a global inhibitory effect while the term forces the network to minimize the distance between two adjacent cities in the tour.

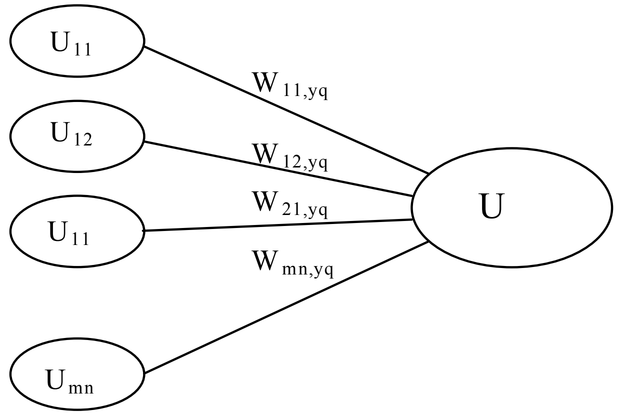


Figure 3. The Hhopfield Network Updating Process.

NEURAL NETWORK MODELING FOR EXPANSION POLICY

Considering the demand loads as cities and the power plant centers as a position in a tour modified Hopfiels neural network can be applied to expansion policy of power plants in different areas. In this case, the constraint include:

a) Each demand load had better assigned to only one plant center.
b) All demand loads should be allocated to the power plant centers.

The major object is to minimize the total investment and operational costs. By comparing the T.S.P and expansion policy of power plant centers , the following can be observed:

1) In the T.S.P, each city can be visited only once. This is similar to the constraint of assigning one demand load to only one power plant center.
2) In the T.S.P, no more than one city can be assigned to a single position, but in the expansion policy problem, it is allowed to assign more that one demand to a power plant center.
3) The T.S.P requires that all the cities should be visited which is similar to the requirement that all demand loads must be assigned to the power plant center in expansion policy.
4) The objective function of T.S.P is to minimize the total travel distance while in expansion policy problem is to minimize the investment and operational costs.

The expansion policy power plant center problem in the context of the Hopfield network can be illustrated in Figure 4. In this sample we have two regions as a demander and five power plant centers, which two of them are candidate for expanding in future. We want to built expansion policy base on T=3 periods. Region one dose not have any increasing demand load in period three. In this case:

a) Shows a feasible solution with allocating region load of demand one of region1 and demand load of period one of region2 to center 2 and the remaining three demand loads to another. Minimum cost of investment and operational cost can be occurred when we expand exactly center two and three.
b) Shows a feasible solution with splitting demand load of period 2 of region1 between center two and three because of expansion constraint or reducing cost.
c) Shows an infeasible solution where demand load of period3 of region2 in row5 is empty – no active neurons i.e., this demand load is not assigned to any center.

Based on the above observation, the first and third term in the T.S.P energy functions are adopted for expansion policy. The last term is modified to reflect the objective of the expansion policy problem. The energy function and the associated connection weight equation are as follow:

$$E=\tfrac{1}{2} A\sum_{Xt}\sum_{R}\sum_{Q} U_{XtRt} U_{XtQt} + \tfrac{1}{2} B \sum_{R}\sum_{t} \Big(\sum_{X}\sum_{Y} 1- U_{XtRt} U_{YtRt} (\hat{e}_{XtRt} + \hat{e}_{YtRt}) /H_t \Big)+\tfrac{1}{2} C \Big(\sum_{X}\sum_{t}\sum_{R} U_{XtRt} - M\Big)^2 +\tfrac{1}{2} D \sum_{t} 1/INV \Big\{\sum_{R}\sum_{X}\sum_{Y} U_{XtRt} U_{YtRt} (IC_{Rt} +PC_{Rt} (T-t+1))\Big\}$$

$R<>Q$ $X<>Y$

IC_{Rt} = fix investment cost of one unit generated power in region R in period t.

PC_{Rt} = operational cost of one unit generated power in region R in period t.

H_t = upper limit of expansion capacity of power plant in any region in each period t.

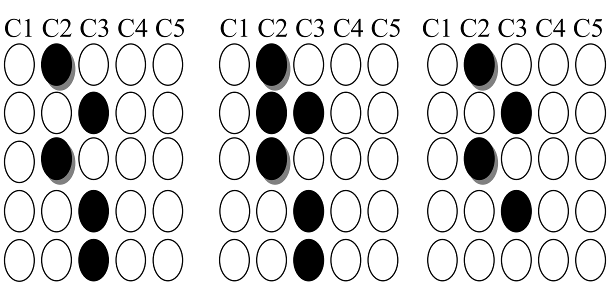
M = number of regions multiply number of periods.

$\hat{e}_{XtRt}$ =demand of region X in period t satisfied by center R in period t

$\delta_{YtQt} =\sum_t\sum_X\sum_R U_{XtRt} .W_{XtRt,YtQt} \quad \forall$ Y ,T,Q

U_{YtQt} ={1 if $\Gamma_{YtQt}>=0$, 0 otherwise }

δ_{RtQt} ={1 if Rt=Qt , 0 otherwise }



[a] [b] [c]

Figure 4. The Expansion Policy with T=3.

TABLE 1. The Comparison Between N.N, and Bender Decomposition Problem.

MODEL	No. OF YEAR	No. OF REGION	No. OF CENTER	Neural Net. Model (cpu time) h:m:s	Benders decomposition (cpu time) h:m:s
I	5	4	4	0:00:01.20	0:00:12.85
II	5	4	4	0:00:01.45	0:05:28.50
III	5	4	4	0:00:01.12	0:00:47.18
IV	5	4	4	0:00:00.55	0:00:45.60
V	7	4	4	0:00:02.40	0:00:48.23
VI	9	4	4	0:00:45.32	0:12:08.25
VII	10	5	5	0:01:15.20	2:02:11.27
VIII	10	5	5	0:02:00.03	2:36:15.16
IX	8	8	8	0:05:30.01	3:48:00.00

δ_{XtYtt} ={1 if Xt=Yt , o otherwise }
$W_{XtRt,YtQt} = - A\ \delta_{XtYt}\ (1- \delta_{RtQt}) + B\ \delta_{RtQt}\ (ê_{XtRt} + ê_{YtQt})/H_t - C\ - D\ S_{XtYt}$
$S_{XtYt} = \{\ \delta_{RtQt}(ê_{XtRt} + ê_{YtQt}\ )(IC_{Rt} +\delta_{Rt}(T-t+1)+(1-\delta_{RtQt}\ )\ (ê_{XtRt}\ (IC_{Rt}+PC_{RT}.T) + ê_{YtQt}\ (IC_{Qt}+PC_{Qt}.T))\}$

The S value can be obtained from load distribution matrix (initial solution). The solution doses not depend on the initial load distribution matrix presentation or data input sequence. To initialize the expansion policy process, the number of center is set to be equal the "number of periods of study" multiple by "number of regions". Then only one demand load in specific period is assigned to each center. The above-mentioned updating procedure can be used to minimize the energy of the network, but the solution could be a local minimum. After reaching a stable state, the actual number of centers is equal to number of center that have at least one active neuron. The expansion policy algorithm can be summarized as follow:

Step 1 A) read A, ∇A, B, ∇B, C, ∇C, D, ∇D, R, C, T, G and calculate S, W.
B) Initialize the network with one region to one center.

Step 2 Update network states until a stable states attained.

Step 3 if any region is assigned to more than one center, discard the current solution and set A = A-∇A, and go to step one. If total assigned load in Tth period is more than H, discard the current solution, set B= B+ ∇B, and go to step one. If the total number of active neurons is less than R, discard the current solution and set C = C-∇C and go to 2 in Step 1.

Step 4 If G equal number of center, stop. Else go to next step.

Step 5 discard the current solution, If G> number of center, set D=D+∇D other wise, set D=D-∇D go to 2 Step 1

RESULTE

The above-presented problem essentially is a mixed integer programming. The integer variables are the complicating variables that make the problem so difficult to solve and when the scale of model is large, NP hard problem arises. In this paper an example designed was solved by neural network and compare with mixed integer programming results. Although adjusting the parameters of neural model takes time, finding the result of model is more faster than that in the backtracking method and mixed integer method algorithms, such as branch and bound, benders decompositions.

In mixed integer programming, it is necessary that the number of the centers as an input to the model be defined, but in this paper the number of the centers is assigned based on the optimal investment and operational cost. As follow the result of neural network modeling compare with bender decomposition in C.P.U time for nine different models in number of region, number of center and number of year. The Information of those models is provided by NSERC, Canada.

CONCLUSION

This paper makes an approach to find optimum number of centers and Optimum distribution power respect to minimizing fixed investment and operational cost, along with others economical and environmental objective functions in long term as an expansion policy of power plant centers. This approach is neural network and it has ability to work without training phase.

The results of neural network in all models, which provided by NSERC, Canada are better than those in Bender's decomposition method. Although the neural network reduces time processing, it has problem with initial network. Future researches include further development of the model and the algorithm of initializing network.

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