The chaotic dynamics is very complicated, and it has Several characteristic properties.

One of them is self-similarity, which indicates that attractors of chaotic dynamical systems usually have fractal structures.

Then, the chaotic dynamics searches solutions only along such a fractal attractor possibly with zero Lebesgue measure in a state space.

Therefore, the chaotic search is expected to be efficient, if good solutions are embedded in a searching region.

On the other hand, stochastic methods search solu-tions without such a deterministic structure.

Thus, the chaotic search can be more efficient than the stochastic searches in this sense.

Moreover, Chen and Aihara (1999,2000) showed that every solution including the optimum one can be included in a strange attractor of the chaotic neural network under some conditions.

Therefore, this kind of dynamics of the chaotic neural network may be very effective for searching of the solutions of combinatorial optimization problems if the structure of a strange attractor can be appropriately designed.

Unfortunately, these approaches (Chen & Aihara, 1995; Hasegawa et al., 1995; Nozawa, 1992; Yamada & Aihara, 1997) based on the architecture of the Hopfield-Tank neural network are not so effective for large for large scale TSPs.

The first reason is that the size of the neural network becomes too large for lager problems.

In the case of solving an n-city TSP, the number of neurons N necessary for the network is

n² in this approach.

Furthermore, since the neurons are mutually connected, the number of mutual connections becomes the order of N² = n⁴.

If the number of cities n increases, the number of mutual connections becomes huge and consequently, calculation gets difficult. As the second reason, if is not easy to construct a closed feasible tour for satisfying the constraint of the TSP such that start-ing from a city, visiting each city exactly once, and return-ing to the starting city.

This is because the closed tour is realized only by firing patterns that completely satisfy this constraint term of the quasi-energy function.

If the state of neural networks does not satisfy the constraint term, it cannot form even a closed feasible tour.

Because of the above reasons, it is widely acknowledged that these approaches based on the architecture of the Hopfield-Tank neural network are applicable only to very small toy problems, such as 10-city TSPs.

In order to overcome the above drawbacks, we have already proposed a novel chaotic searching method (Hasegawa, & Aihara, 1997), which is not based on the Hopfield-Tank neural network.

We combined the dynamics of the chaotic neural network with the 2-opt algo-rithm which is a very simple updating method of the tour of the TSP.

Because the 2-opt algorithm always produces a feasible tour, this method (Hasegawa et al., 1997) always offers feasible solutions.

Moreover, since the method does not use a basic coding scheme proposed by Hopfield and Tank (1985), decreasing the tour length and satisfying the constraint are not implemented into mutual connections.

Namely, there are no important connections between neurons.

Consequently, computation is much easier than the conventional chaotic approaches (Chen & Aihara, 1995; Hasegawa et al., 1995; Nozawa, 1992; Yamada & Aihara, 1997).

Then, we showed that this method is applic-able to larger problems, for example several hundred-city problems (Hasegawa et al., 1997).

On the other hand, there are still various efficient methods for large TSPs.

Among them, the tabu search is recognized as one of the strongest methods in recent studies (Glover, 1989, 1990; Glover, Taillard, & Werra, 1993).

The concept of the tabu search is so described that it forbids moves which have recently been done, then possibly searches other regions in a searching space.

The algorithm of the tabu search is described as follows: if there are no improving moves, it described as follows: if there are no improving moves, it chooses the move that least degrades the objective function value.

In order to avoid returning to the local opti-mum just visited, reverse moves are perfectly forbidden.

This is realized by storing those moves in a data structure called a tabu list. It contains s elements which memorize forbidden moves, where s is the tabu list size.

Once a move was stored in the tabu list it should be tabu for s iterations.

This tabu move will be available again, s iterations later.

Form the viewpoint of the ‘tabu effect’ that forbids backward moves, the chaotic neural network model (Aihara, 1990; Aihara et al., 1990) has a similar effect to the tabu search.

The reason is that the chaotic neural network, which is based on the Caianiello neuron model (Caianiello, 1961) and the Nagumo-Sato neuron model (Nagumo & Sato, 1972), includes temporal summation of refractory effects.

This effect is one of the characteristics of real biological neurons; neurons become hard to fire after previous firings.

Then, we find it possible to implement the tabu effect by a neural network with this refractory effect, if neurons inhib-ited by the refractory effect correspond to the tabu moves (Hasegawa, Ikeguchi, & Aihara, 2000).

In addition to such characteristics, the chaotic neural network also has complex analog chaotic dynamics, which may provide higher search-ing abilities for combinatorial optimization problems.

This method can be realized by extending the conven-tional tabu search to chaotic versions.

First, the tabu search is implemented on a neural network.

The refractory effects of each neuron are substituted for the tabu effect of the tabu search.

Namely, every possible heuristic move is defined by a firing of a neuron, and each neuron has refractory effects after its firings.

In this neural network, a large refractory effect of some neuron means that the corresponding move is tabu.

This neural network can realize the same algorithm as the conventional tabu search, which we call the tabu search neural network.

Second, each neuron is replaced by the chaotic neuron (Aihara, 1990; Aihara et al., 1990).

A different point between the tabu search neural network and its extension to the chaotic version is that these two networks have different output functions.

The states of the tabu search are determined to be alternatively tabu or non-tabu, and then the tabu search neural network expresses all the states by 0 or 1 state neurons.

On the other hand, the chaotic neuron has a non-linear analog output function and refractory effects which comprise chaotic dynamics.

We utilize this type of chaotic dynamics that can preserve the tabu effect.