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Development of System Framework for Smart Cities with Forecasting Electrical Consumption

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Abstract: ***A significant extent of world energy consumption is by creating nations. Today, electric energy has turned into a basic and fundamental piece of the improvement of technology.. Generation and consumption of electrical energy, which encourages human life and builds work efficiency, are expanding each year. The artificial neural networks (ANNs) received attention in control applications due to the ability to produce complex dynamics, especially when they have feedback connections. The problem of finding the best parameter set for a network to solve a problem can be seen as a search and optimization problem In recent past, there are two widely used stochastic algorithms, genetic algorithms (GAs) and particle swarm optimization (PSO), applied to the problem of optimizing parameters of ANNs for the training of different research datasets.. ANN appears to be a decent indicator of electricity consumption***.

1. Introduction

Artificial Neural Networks (ANNs) are system composed of neurons organized in input, output, and hidden layers. The neurons are connected to each other by a set of synaptic weights. An ANN is a powerful tool that has been applied in a broad range of problems such as pattern recognition, forecasting, and regression. During the learning process, the ANN continuously changes their synaptic values until the acquired knowledge is sufficient (until a specific number of iterations is reached or until a goal error value is achieved). When the learning process or the training stage has finished, it is mandatory to evaluate the generalization capabilities of the ANN using samples of the problem, different to those used during the training stage. Finally, it is expected that the ANN can classify with an acceptable accuracy the patterns from a particular problem during the training and testing stage. Several classic algorithms to train an ANN have been proposed and developed in the last years. However, many of them can stay trapped in non desirable solutions; that is, they will be far from the optimum or the best solution. Moreover, most of these algorithms cannot explore multimodal and noncontinuous surfaces

1.1 Purpose and Importance of Thesis

The purpose of this research work is to present novel optimization algorithm called AAA to improve the ANN performance

1.2 Swarm Resources

Swarm Intelligence is the study of computational systems inspired by the 'collective intelligence'. Collective Intelligence emerges through the cooperation of large numbers of homogeneous agents in the environment. The paradigm consists of two dominant sub-fields 1) Ant Colony Optimization (ACO) that investigates probabilistic algorithms inspired by the stigmergy and foraging behavior of ants, and 2) Particle Swarm Optimization (PSO) that investigates probabilistic algorithms inspired by the flocking, schooling and herding. Like evolutionary computation

1.2.1 ACO

Ant colony optimization (Dorigo, Maniezzo and Colorni 1991; Dorigo and Stützle 2004) is a population-based metaheuristic that can be used to find approximate solutions to difficult optimization problems.

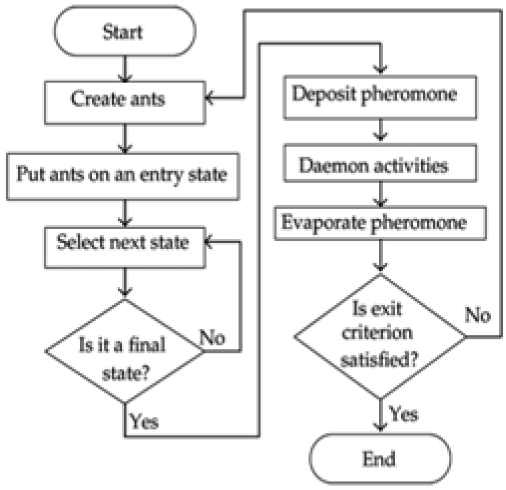

Figure 1.1: Flowchart of ACO

1.2.2 PSO

Inspired by the flocking and schooling patterns of birds and fish, Particle Swarm Optimization (PSO) was invented by Russell Eberhart and James Kennedy in 1995. Originally, these two started out developing computer software simulations of birds flocking around food sources, and then later realized how well their algorithms worked on optimization problems

The algorithm keeps track of three global variable

- Target value or condition_

_Global best (gBest) value indicating which particle's data is currently closest to the Target

_Stopping value indicating when the algorithm should stop if the Target isn't found.

It's also common to see PSO algorithms using population topologies, or "neighborhoods", which can be smaller, localized subsets of the global best value

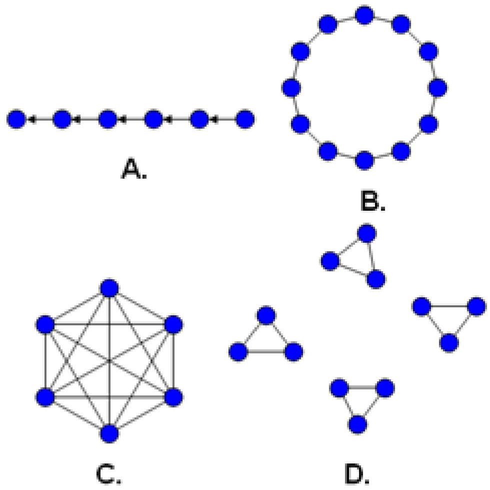

Figure 1.2: A few common population topologies (neighborhoods)

a) Single-sighted, where individuals only compare themselves to the next best.
b) Ring topology, where each individual compares only to those to the left and right.
c) Fully connected topology, where everyone is compared together.
d) Isolated, where individuals only compare to those within specified group Neighborhoods definitions and how they're used have different effects on the behavior of the algorithm. The Basic PSO Algorithm is explored in diagram followed by pseudo code

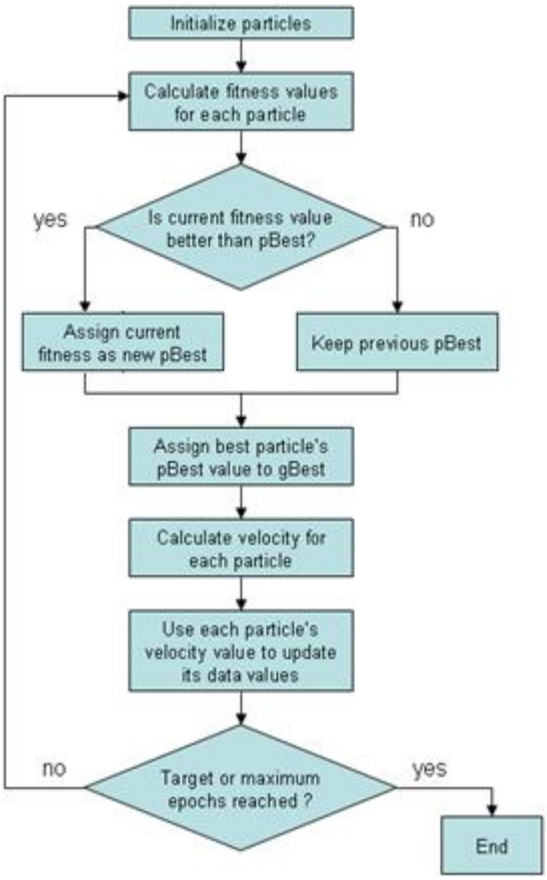

Figure 1.3: Flow diagram illustrating the particle swarm optimization algorithm

2. Materials and Method

This dataset is originally from the Individual household electric power consumption Data Set.

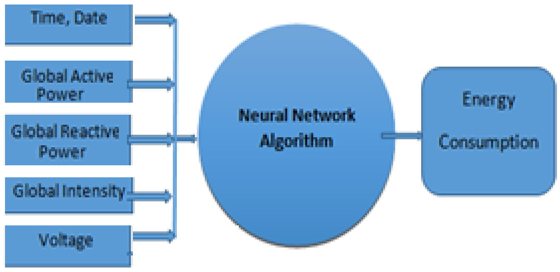

Figure 2.1: Prediction of energy consumption

2.1 Training of Artificial Neural Networks

Artificial neural networks (ANNs) or connectionist systems are computing systems inspired by the biological neural networks that constitute animal brains.

2.1.1 Training Artificial Neural Networks with Particle Swarm Optimization

PSO, one of the population-based heuristic optimization methods, was first developed by Kennedy and Eberhart in 1995, inspired by social behavior in flocks of birds or schools of fish while finding food.

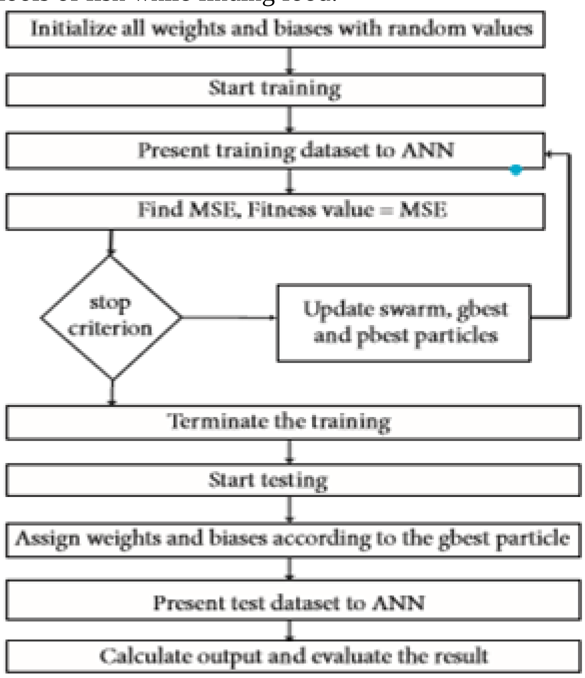

Figure 3.1: Flowchart for the training and testing of the PSONN

Table 3.1: Equations used in PSONNs

PSONN model	Velocity update Eq. No	Inertia weight Eq. No.	Constriction factor Eq. No.
PSONN1	Eq. (3.2)	-	-
PSONN2	Eq. (3.3)	Eq.(3.3)	-
PSONN3	Eq. (3.4)	Eq.(3.5)	-
PSONN4	Eq. (3.6)	-	Eq.(3.7) and Eq. (3.9)
PSONN5	Eq. (3.7)	-	Eq.(3.8) and Eq.(3.9)
PSONN6	Eq. (3.10)	-	Eq.(3.7) and Eq. (3.9)
PSONN7	Eq. (3.10)	-	Eq.(3.8) and Eq. (3.9)

2.2 Training Artificial Neural Networks with Artificial Algae Algorithm

Artificial algae algorithm (AAA), which is one of the recently developed bio-inspired optimization algorithms, has been introduced by inspiration from living behavior of microalgae.

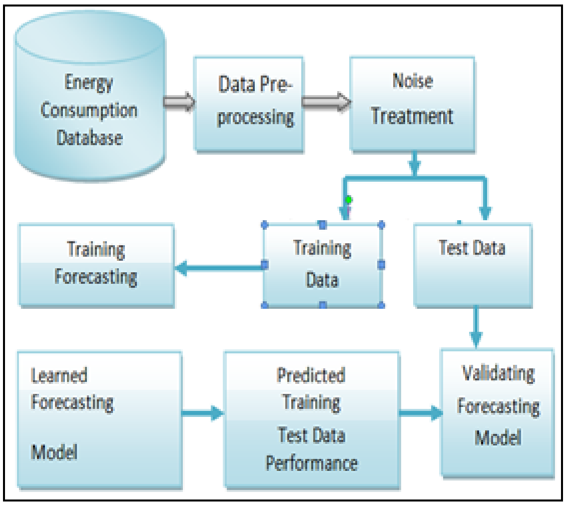

Figure 3.3: Energy predication in artificial neural networks

3. Results and Suggestions

This chapter presents the extensive simulation results for methods investigated in this project such as ANN-PSO and ANN-AAA by using two research data sources such as energy consumption .

3.1 Comparative Results

Result Analysis for Prediction of the energy 5.1.1 consumption. We used the 70 % training and 30 % testing scenario with varying number of hidden layers such as 5, 10 and 15 for both ANN-PSO and ANN-AAA.

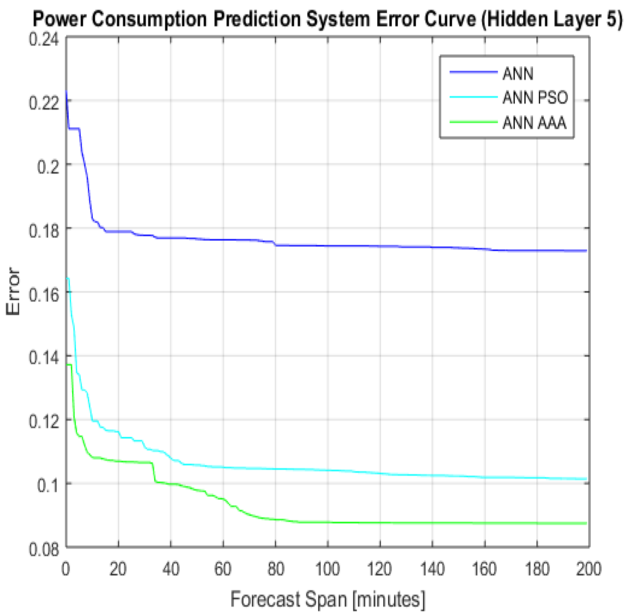

Figure 5.1: Power Consumption Prediction System Error Curve (HL5)

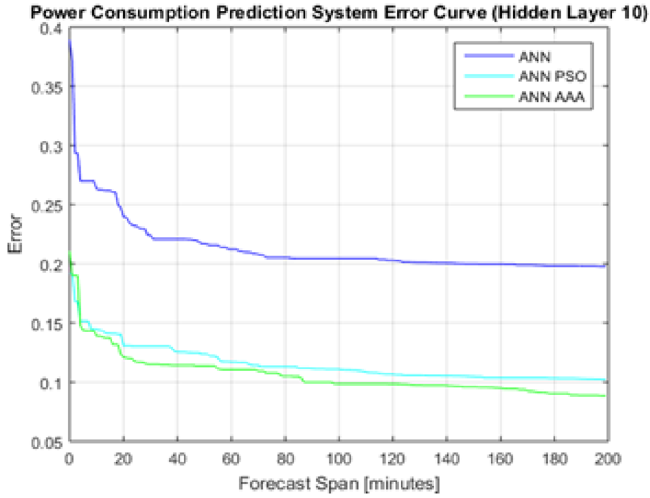

Figure 5.2: Power Consumption Prediction System Error Curve (HL10)

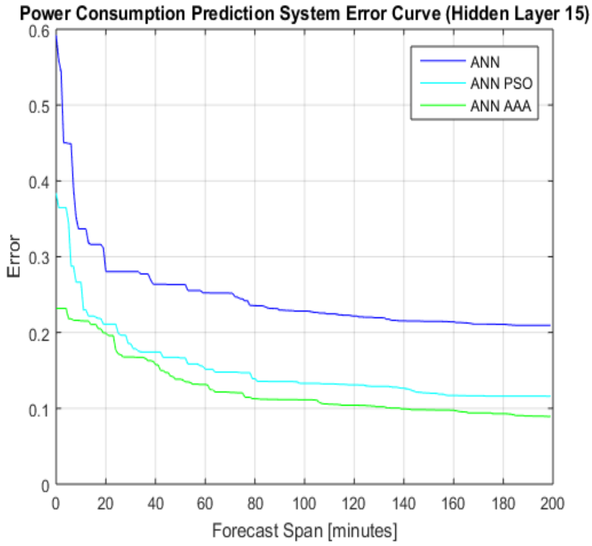

Figure 5.3: Power Consumption Prediction System Error Curve (HL15)

As show in figure 5.4 training accuracy rate analyses for power consumption forecasting. According table 5.1 there are 5, 10, 15 numbers of hidden layers to shown ANN, ANN-PSO, As result present ANN is better as compare to others ANN-PSO and ANN-AAA

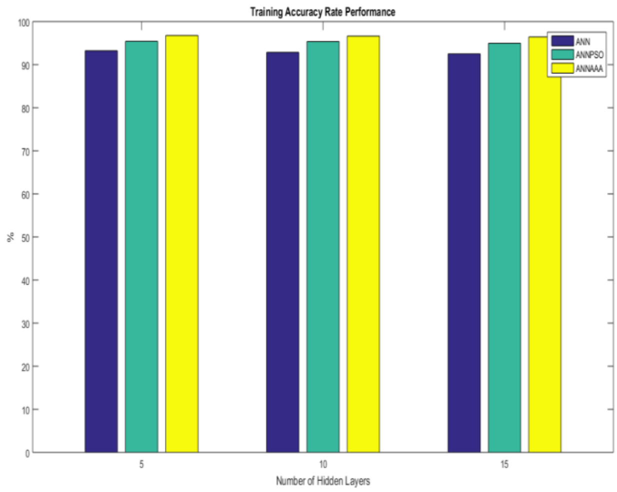

Figure 5.4: Training accuracy rate analysis for power consumption forecasting

Table 5.1: Training accuracy rate analysis for power consumption forecasting

Hidden layers	ANN	ANN-PSO	AAA-ANN
5	93.2331	95.4316	96.7664
10	92.8622	95.3433	96.6354
15	92.5119	94.9700	96.444

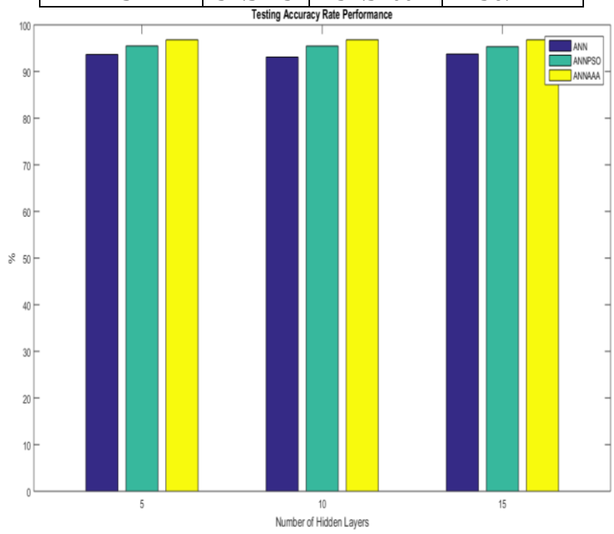

Figure 5.5: Testing accuracy rate analysis for power consumption forecasting.

Table 5.2: Testing accuracy rate analysis for power consumption forecasting

Hidden layers	ANN	ANN-PSO	AAA-ANN
5	93.6454	95.4861	96.8252
10	93.1041	95.4763	96.8152
15	96.8072	95.3415	96.8072

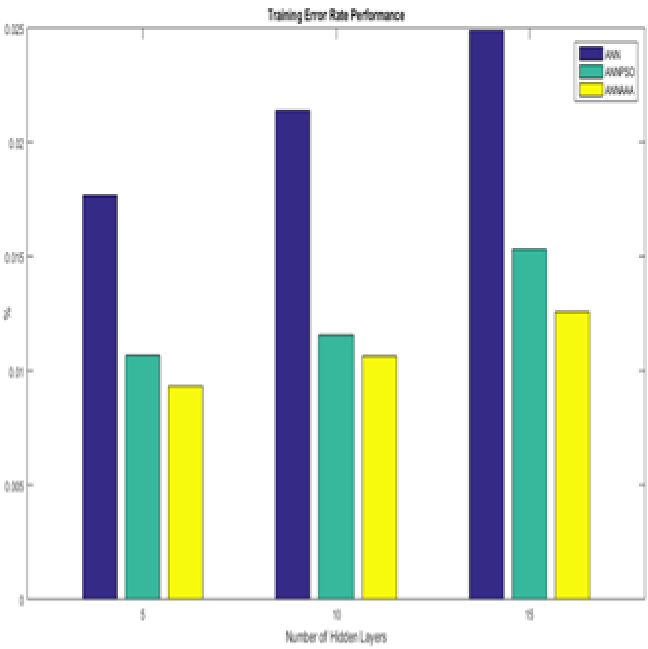

Figure 5.6: Training error rate analysis for power consumption forecasting

Table 5.3: Training error rate analysis for power consumption forecasting

Hidden layers	ANN	ANN-PSO	AAA-ANN
5	0.0177	0.0107	0.0093
10	0.0214	0.0116	0.0106
15	0.0249	0.0153	0.0126

4. Conclusion

Householders' profiles and examples will enable electricity providers to get customers' conduct, set up progressively adaptable and redid electricity costs to maintain a strategic distance from pinnacle consumption. Then again, presumes will profit by the forecasting arrangements that will gauge the wind and PV age, along these lines they will plan their machines as indicated by electricity costs and their age assets. From our tests, , it is important to re-arrange the ANN parameters. Favorable position of artificial neural networks if there should be an occurrence of consumption and age forecasting is that they perform expectations with excellent results in a brief span, which makes ANN, is especially helpful for continuous momentary forecasting.

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