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Improving Lifetime of Strategic Information Network in Oil Supply Chain

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Abstract

Today, information networks play an important role in supply chain management. Therefore, in this article, clustering-based routing protocols, which are one of the most important ways to reduce energy consumption in wireless sensor networks, are used to optimize the supply chain informational cloud network. Accordingly, first, a clustering protocol is presented using self-organizing map neural network, SOM. Second, we cluster the network nodes based on two criteria of neighborhood and energy level using K-means clustering pattern. Third, we survey the efficiency and inefficiency of the clusters to balance the energy properly among the clusters. Then, to increase the network lifetime and to maintain the network DEA method is used. Finally, the model is tested for the information network of oil supply chain.

Keywords: Strategy, Neural Network, Energy, Clustering, DEA

Introduction

In today's completive markets, companies need to identify and exchange knowledge and findings regarding their supply chain to survive, develop, and stay competitive. Typically, there are three main flows in a supply chain:

- Materials' flow which includes ready products, raw materials, lateral materials, returned materials and products and other production supplies.
- Strategic informational flow that includes the information flow of data related to amount of demand, supply, orders, returns, planning and changes in data.
- Financial flow, which includes money transfers, kinds of payments, the suppliers and customers' credit cards information and information related to the customers' financial flows.

Undoubtedly, the information flow is more important than two other flows for the supply chain of the corporations in current conditions. Informational networks of extranet, intranet, internet, and so on are very important for the corporations to run a supply chain. Progress in technology and creation of microcircuits have made it possible to use wireless and cloud circuits in most electronic devices to share information. The progress has also led to the development of tiny-sensors. The tiny-sensors can perform various functions such as refining exact information, increasing internal network power of an organization and so on. In recent years, organizations have been able to transfer information along the chain utilizing a cloud network. Hence, sharing information through networks in supply chain has been developed significantly it can be observed in supply chain of oil industry.

Accordingly, the goal of this article is to present a more optimal algorithm, which first, may reduce energy consumption in informational sensor network of supply chain. Second, it may enable to maintain maximum lifetime of a sensor network. Finally, it may help rank the clusters according to the efficiency level of the clusters.

The article is structured as follows: research background and literature review, research methodology, findings, proposed model, and finally, the results.

Research Background and Literature Review

The Role of Neural Networks in Reducing Energy Consumption of Cloud Networks

Artificial neural network is a large system of distributed or parallel processing components called Neurons or nervous cells connected together in a topology graph. In wireless sensor networks, platforms with unpredictable and fuzzy nature and different parameters influence their behavior. Neural networks can reduce communications and save energy through reducing dimensions of data, which is obtained simply from neural networks clustering algorithms (Arya Nejad 2004).

Clustering by SOM Neural Network

SOM

model works in two modes as other neural networks: training and mapping. The training stage makes the map using input examples. Making map is a competitive process and it is performed based on vector measurement. The process includes the following:

1. Weights of each output nodes are identified according to the relationships1 to 3
2. Random vector is selected from training data and is placed in **SOM**.

3. The best matching unit **BMU** is found by computing distance between input vector and communicative weights of each output node according to the relationship 4.
4. The neighborhood radius around the best matching unit is computed by considered neighborhood function. The size of neighborhood is decreased by increasing the time of algorithm according to relationship 5 and 6.
5. Each node in the neighborhood of the best matching unit sets updates its communicative weights according to the relationship 8 and 9 to better resemble the best matching unit. The weights of the nodes closer to the best matching unit undergo more changes than those farther from it.
6. The stages 2 to 6 repeat so that. the weight vectors get stable, i.e. stop changing.

The best matching unit is computed based on Euclidian distance between weight vectors of output nodes and input vector values. Actually, Euclidian distance is a criterion to measure the similarity between two sets of data. The neighborhood radius is decreased in each repetition of training algorithm, so that finally, it includes only the best matching unit. Neighborhood is usually specified by a Gaussian or exponential function, as the nodes closer to the carrier unit BMU are influenced more than the farther nodes. In addition, learning rate coefficient of an exponential function, received according to the relation 10, will ensure **SOM** convergence. Then, in mapping stage, **SOM** ranks each new input vector automatically.

The features that we want to consider as **SOM** input data set in proposed algorithm are **x** and **y** coordinates of each node in network space and energy level of each node **X, Y,E**. Thus, we have **D** matrix in dimension of $3 \times n$ since, we want to apply two different variables o to the network. Accordingly, first, we must normalize the values to have integrated data for the problem. We use min-max normalization method in the research where $\mathbf{min_a}$ and $\mathbf{max_a}$ are min and max values for the feature of a. Min-max normalization, maps the value of **v** in the range of Zero and One.

$$V' = \frac{v - \min_a}{(\max_a - \min_a)} \tag{1}$$

So, by the relationship 1, our data set matrix is as follows:

$$D = \begin{bmatrix} \frac{xd_1}{xd_{\max}} & \frac{yd_1}{yd_{\max}} & \frac{E_1}{E_{\max}} \\ . & . & . \\ . & . & . \\ . & . & . \\ \frac{xd_n}{xd_{\max}} & \frac{yd_1}{yd_{\max}} & \frac{E_n}{E_{\max}} \end{bmatrix} \tag{2}$$

In the above relationship, **D** is data sample matrix or **SOM** neural network input vectors, $XD=xd_1...x_{dn}$ are **X** coordinates, YD= $yd_1…y\ d_n$ are **Y** coordinates, E= $E_1…E_n$ is energy level of the remained energy of the network nodes, xd_{max} is max value for **X** coordinates and yd_{max} is max value for **Y** coordinates of the network space and E_{max} is the remained energy of the network node, which includes the highest energy level at the beginning. The remained energy algorithm equals the initial energy $E_{Initial}$. The important point here is the number the

SOM learning algorithm must be performed to get to convergence.

This repetition number itself is a category. Previous researches failed to present a single number or formula for it. Therefore, we have measured the following repetition umber for **SOM** neural network training and mapping:

EPOCH=1000 rounds (3)

Epoch is frequency number of the learning algorithm performance. To specify the weight matrix, **m** node should be selected as a network space. Due to **SOM-Kmeans** two-stage clustering method, it is necessary, especially in wide sensor networks, to consider a relatively large value for**m**. In this case, we can select **m** nodes randomly and/or we can apply a reasonable value to it. The **m** number is the number of homes, which we consider for an N-dimension space.

In this study training is carried out through minimizing Euclidian distance between input samples and the map initial samples which are weighed by $h_{i,j}$ neighborhood function. Thus, the criterion, which must be minimized, is defined as below (Eshaghi 2009).

$$E_{SOM} = \frac{1}{N}\sum_{k=1}^{N}\sum_{j=1}^{M} h_{j,N(X^{(k)})}\left\|w_{.j} - x^{(k)}\right\|^2 \tag{4}$$

In the above relation, **N** is data sample number, **M** is a map unit number, Nx^k is a neural cell with the nearest distance from Nx^k data sample. Based on the above relation Gaussian neighborhood function is defined as relationship 5 below:

$$h_{i,j}(t) = \exp\left(-\frac{\left\| r_j - r_i \right\|^2}{2 ±_t^2}\right) \tag{5}$$

In which, $\left\|r_j - r_i\right\|^2$ is the distance between the map unit of j and input sample i and $±_t$ is the neighborhood function at the time of t, which is defined as follows:

$$±(t) = ±_0 \exp\left(-t/T\right) \tag{6}$$

In which t is a training repetition number, T is the maximum repetition number or training duration. It is computed considering the distance between X_k and weight vectors of all the neural cells of the map. If the cell N X_k has the lowest distance with input sample X_k, it wins the competition stage:

$$N(X_k) = \arg\min_{1 < j \le m} \left\|W_{.j} - X_k\right\|^2 \tag{7}$$

After the competition stage, SOM must update the carrier cell N X_k weight vector and all its neighbor cells which have been located in R ^{NXk} neighborhood radius. If $W_{.j} \in R^{N(X_k)}$

(8)

Then

$$W_{.j}(t+1) = W_{.j}(t) + \sim(t) h_{j,N(x_k)}(t)_k (x(t) - W_{.j}(t))$$

$$W_{.j}(t+1) = W_{.j}(t) \tag{9}$$

In the above mentioned relations, $h_{j,N(X_k)}(t)$ is the neighborhood function at the time of t and $\sim(t)$ is the training linear factor at the time of t which is defined as below:

$$\sim(t) = \sim_0 (1 - t/T) \tag{10}$$

In this relation, α_0 is the initial training rate, t is the training algorithm repetition number and T is the maximum training duration or repetition. The training stage repeats until weight vectors become stable, i.e. until there is no change in the weight of inputs. After training stage, self-organizing map neural network, will be able to cluster n data sample in the form of m map cluster unit.

Clustering by K-means algorithm

K-means algorithm divides data set into k-subset cluster. As all the members of each subset include the nearest distance from the center of the subset, K-means selects the object k input sample randomly as the centers of the clusters. Then, it assigns other objects input samples based on the least Euclidian distance from the centers of the specified clusters to the proper clusters. Afterwards, the average of each cluster is computed again and is considered as a new center of the clusters. The operations repeat until the centers of the clusters stop changing.

The criterion must be minimized in K-means:

$$E_{K-means} = \frac{1}{C}\sum_{k=1}^{C}\sum_{x\in Q_k}\left\|x - C_k\right\|^2 \qquad (11)$$

In the above relation, C is the number of the clusters Q_k and K-cluster, and C_k is the center of the cluster Q_k.

The important point here, is to find out the best value for K optimal number of the clusters.

There are various methods for specifying the optimal number of clusters. We use three of them:

1. Randomly
2. Based on the required number of cluster-heads
3. Index called Davies Bolden which computes intra-cluster dispersion ratio to inter-cluster distances through the following relation:

$$I_{DB} = \frac{1}{C}\sum_{k=1}^{C}\max_{l\neq k}\left\{\frac{S_c(Q_k)+S_c(Q_l)}{d_{ce}(Q_k,Q_l)}\right\} \qquad (12)$$

$$S_c(Q_k) = \frac{\sum_i \left\|x_i - c_k\right\|^2}{\left|Q_k\right|}$$

In which:

$$d_{cl}(Q_k, Q_l) = \left\|c_k - c_l\right\|^2 \qquad (13)$$

C is the number of clusters, S_c is an intra-cluster dispersion, and d_{cl} is a distance between the centers of two clusters k and l.

Small values of Davies Bolden's index are related to the clusters that are compressed and their centers are separated completely from each other. As a result, the number of clusters which minimizes Davies Bolden's index is considered as the optimal number of clusters (Jafar Nejad et al 2007).

Data Envelopment Analysis

A criterion called Efficiency is used to evaluate the performance of each unit, clusters, and in each set, in which an activity is performed. However, the criterion of Efficiency helps us evaluate not only the performance but also the quality (Jahan Shahlou 2010).

The economic efficiency of DMUρ is defined as below (Jahan Shahlou 2006) if the system under evaluation includes n "decision-making" unit $DMU_1, DMU_2, ..., DMU_¸$ in which each DMUj consumes m-input $X = (x_{1j}, x_{2j}, ..., x_{mj})$ to produce s-output $Y = (y_{1j}, y_{2j}, ..., y_{sj})$. Inputs and outputs of each DMU are all non-negative and each DMU has at least one positive input and one positive output.

$$\text{Efficiency} = \frac{\sum_{r=1}^{s} u_r y_{r\circ}}{\sum_{i=1}^{m} v_i x_i} \qquad (14)$$

In this case, decision-making units are easily comparable. However, since the cost of inputs and price of outputs are not always available and exact, we use DEA models in general mode. After Charnes, Cooper and Rhodes presented the model CCR, it became the basis and foundation of Data Envelopment Analysis DEA, a branch in the operational research (Hussein Zade 2008). In addition to CCR model, other models such as BCC, RAM, SBM, additive model, and FDH were introduced later to strengthen DEA. Some of the models are discussed briefly in this study.

The first proposed model is a non-linear model, which can be expressed by the following linear equivalent (Darvish Motevalli 2008).

(15)

$$
\begin{array}{lll}
E_{\circ} = \max \sum_{r=1}^{s} u_r y_{r\circ} & & \\
\quad \sum_{i=1}^{m} v_i x_{i\circ} & & \\
s.t. \quad \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 & ; & j = 1,2,...,n \\
\quad u_r , v_i \geq 0 \quad ; \quad r = 1,2,...,s; & & i = 1,2,...,m
\end{array}
$$

The next model, called Multiplier form of CCR model. is the dual of the form, called Envelopment form of CCR model and is expressed is as follows (Cooler 2006):

(16)

$$
\begin{array}{ll}
\quad Min\bar{} & \\
s.t. \quad \sum_{j=1}^{n} \mathrm{a}_j x_{ij} \leq \bar{} x_{i\circ} & i = 1,2,...,m \\
\quad \sum_{j=1}^{n} \mathrm{a}_j y_{ij} \geq y_{r\circ} & r = 1,2,...,s \\
\quad \mathrm{a}_j \geq 0 & j = 1,2,...,n
\end{array}
$$

Banker, Cooper and Charnels presented BBC model to measure efficiency on fixed scale [٩]/ Anderson and Peterson presented Model AP to rank Efficient Decision Units (Lin 2014).

(17)

$$
\begin{array}{l}
\sum_{i=1}^{m} v_i x_{i0} = 1 \\
\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq o \longrightarrow j = 1,2,...,m \\
u_r , v_i \geq 0
\end{array}
$$

Research History

Various methods have been applied so far to decrease the energy consumption of sensor nodes in particular and cloud or wireless sensor network in general. In some cases, the methods are categorized based on protocol stack layers.. For example, Lu and Wang (2013) have accomplished comprehensive studies on reduction protocols of energy consumption in the layer MAC. In addition, many methods have been used to reduce communications in the network layer called Routing protocols (Matthews 2013). The neural networks have been used for power dynamic management to maximize the lifetime of the sensor nodes after placing and timing the cycle of sensor nodes duties to specify awake or asleep state..

Javadi et al (2011) discussed Topology control protocol based on the place using learning Automata/Atamata for wireless supply chain sensor networks to increase wireless networks lifetime.

Mirhedayatian et al (2104) suggested an efficient energy method in his article to form backbones in wireless supply chain sensor networks aiming to minimize total weight and to find optimum degree limitation simultaneously. The method has great effect on increasing the backbone lifetime. Another study discusses general application of neural networks in sensor network.

$$\max Z_{\circ} = \sum^{s} u_r y_{r\circ}$$

Tseng et al (2009) ranked the environment based on Kohonen self-organizing map and SOM which had the best cell matching. They also studied ranking on sensor data line.

Wang et al (2011) in their study of wireless sensor networks platforms which included fuzzy and unpredictable nature and various parameters found that neural networks could lead to the reduction of communications and save energy through decreasing data dimensions.

Wang and Luo (2006) used ranking methods based on ART neural network to decrease data traffic in the node and as a result, to reduce the energy consumption.

Further, Govindan et al (2013) suggested an organizing method with energy productivity for sensor networks to track the target. The target location is obtained through common sensor by combining multi sensor data. They used a set of features of each sensor as neural network inputs of three-layer reverse publication. The features belonged to a wireless sensor node and using them as neural network inputs could predict the sensor energy level.

Other researchers suggested a new method for routing energy in wireless neural networks in which each wireless node used a self-organizing map neural network to make decision on taking data pack and participating in routing or ignoring the routing.

Jahanshahloo et al (2010) specified the efficiency and ranked the educational groups and units using data envelopment analysis to evaluate the performance of university units of Free Islamic University.

Research Methodology

The considered project is a practical research which will be accomplished using scientific findings on neural networks and data envelopment analysis model regarding clustering the supply chain informational nodes and evaluating the cluster-heads efficiency. This artivle presents a new clustering algorithm, which works based on energy and self-organizing map neural network. A combinational approach of neural network SOM, K-means and data envelopment analysis is used to change the traditional idea of clustering. The major purpose of the approach is to create the initial map of informational nodes by clustering informational cluster-heads and specifying the efficiency of the cluster-heads.

First we have studied the subject literature and similar researches to select a list of variables and indexes important for supply chain sensor networks and their lifetime:. Second, the initial structure of the neural networks has been developed using self-organizing neural networks of **SOM** and its various dimensions have been identified. Third, using information clustering methods and k-means in supply chain sensor networks, the extracted data of the neural network have been clustered with each cluster including several variables representing the lifetime and energy level of the clusters. After specifying the clusters, we started to analyze the performance of the clusters in terms of efficiency. Accordingly, we have developed model based on it using data envelopment analysis **DEA**. Further, the clusters are divided into two categories, efficient and inefficient, according to **DEA** technique. Then, we rank efficient clusters and present strategies to improve inefficient clusters, which weaken the lifetime of the networks.

MATLAB software is used to analyze the data and to cluster the cloud sensor network. **DEA**-Solver Software is applied to specify efficiency and inefficiency of the created clusters in data envelopment analysis.

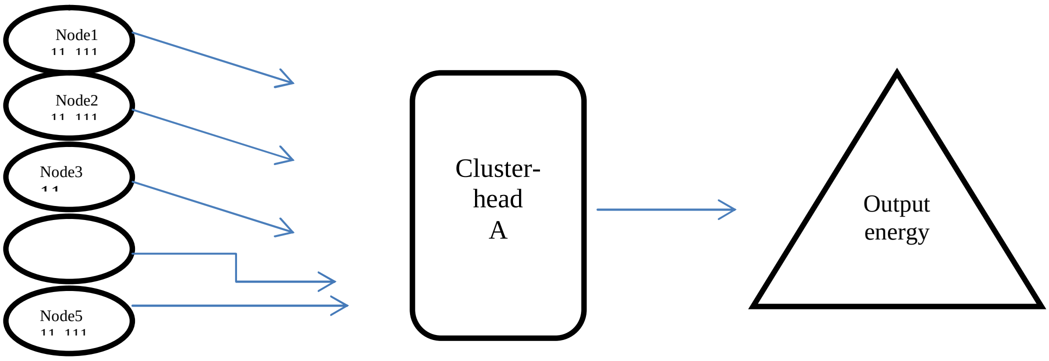

Figure 1. Input and Output Graph (the way of energy inputs and outputs to the main cluster-head)

Research variables

To develop the proposed model oil supply chain informational network has been surveyed and clustered into 1000 random nodes. First, the initial map of geographical points is created and then clustering based on neighborhood points is performed.

Input variables include the energy of five nodes connected to the cluster-head and output variable is outgoing energy of the cluster-head

Proposed Algorithm

The first algorithm is a concentrated clustering method, i.e. the cluster formation and attribution of the related roles to the nodes are accomplished by the base station. The base station is a node usually outside the network, which does not have any limitation in processing and energy resources. The performance of **LEACH** algorithm is divided into several rounds. Each round is started with Setup Phase cluster formation in which the clusters are organized. Following each Setup Phase, Data Transmission Phase is started during which data are transmitted from usual nodes to cluster-heads. Each cluster-head combines received data from member nodes and transmits it in the form of data pack to the base station. The base station is responsible for clustering network nodes and attributing proper roles to them. After specifying the cluster-heads of current round, the base station transmits a message, including the cluster-heads' **ID** of each cluster, to each node. If the cluster-head's **ID** of a node conforms to its **ID**, the node is a cluster-head; otherwise, it is considered a usual node. In addition, for each returning cluster, the base station creates a table for Time Division Multiple Access **TDMA** and the cluster-heads are influenced by the table. **TDMA** table is used for timing the sensor nodes' data transmission and enables the sensor nodes to turn off their radio antenna and save the energy. Therefore, the cost of the energy that is required to form clusters is considered only for the base station and no control pack is transmitted by network nodes. The second algorithm is that the base station posesses enough knowledge about energy level and the state of network nodes, e.g, if each node includes **GPS**. Another important algorithm is that network nodes are distributed randomly in network space.

The current study proposes new protocol that uses two-stage clustering procedures with **SOM** and **K-means.** The following figure illustrates it:

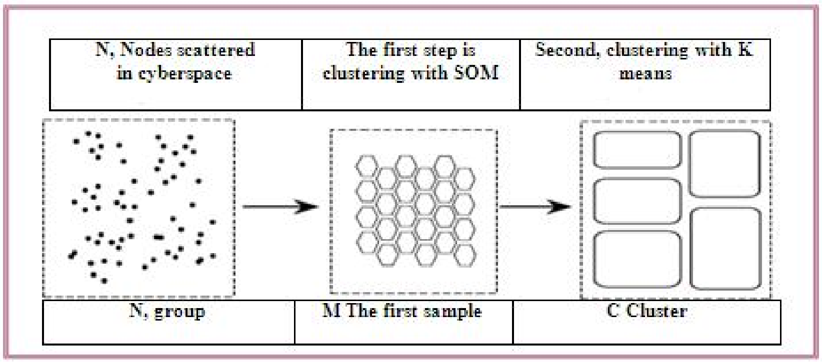

Figure 2. Two-stage clustering with SOM and K-means

The sensor nodes clustering with self-organizing map neural network SOM enables to decrease dimensions of multi-dimensional input data and create visual clustering in the form of a map. Self-organizing map neural network is used as the first stage of sensor nodes clustering to select the data dimensions, then, to categorize and visualize the initial data. After the data is clustered by **SOM** neural network, **SOM** output is clustered again using **K-**means algorithm. It should be mentioned that two-stages clustering has greater advantages for multi dimensional large data sets. Finally, the efficiency of the cluster-heads is evaluated using **DEA** approach.

Model Estimate and Research Findings

In this section the results of the simulation of new clustering algorithm and their comparision with the last clustering protocols are presented. The simulation was performed using MATLAB software to create S**OM** neural networks. Then, K-means algorithm was used for clustering. Finally, the efficiency of the created clusters was evaluated through data envelopment method using **DEA-S**olver software.

Accordingly, in the first stage, we randomly released 350 supply chain informational network sensors to the space with 100x100 dimensions. The results are presented in table 2. We have a **D** matrix with $n \times 3$ dimension. Since we want to apply two different variables to the network, first we must normalize the values to have integrated data for the problem. M is the number of homes in **N-**dimension space. Thus, according to the results presented in the table 1, 80 homes are created in 100x100 spaces and initial clusters will be formed with balanced energy.

Table 1.Clustering by self-organizing map neural network

Paramet er	**Scene 1**
N	**350**
Area	**100x100**
Epoch	**1000**
M	**80**
Initial Energy	**0.5j**
K	**Davies-Bouldin, Random ,Input**
Cluster Head	**Maximum Energy**
Transpor t Data	**1% for Cluster Member & 3% for Cluster Head**

In the second stage, the results of the previous stage are turned into 33 clusters using K-**means** algorithm. Now the base station has optimum number of the clusters and member nodes of each cluster. Next, we must select proper cluster-heads for each cluster and assign suitable roles to each node. The results of the second stage is presented in table 2.

Table 2.Clustring by K-means algorithm

Parameter	Scane 1
N	**350**
Area	**100*100**
Epoch	**1000**
M	**80**
K	**Davies-Bouldin**
Davies-Bouldin	**33**

The research results indicate that the criterion of max energy level gives better results than two other criteria related to the increase of the sensor network lifetime. We use the method **A** in the protocol. The criterion output shows longer lifetime in terms of death time of the last node. A node, which has the highest energy level among its co-cluster nodes, is selected as a cluster-head node. As each of the 33 clusters includes several member nodes, each node, which has the highest energy level, is selected as a cluster-head to communicate with the base station.

MATLAB programming language was used for the tesing and validating the proposed algorithm. The results of the proposed protocol were then compared with the results of similar protocols, namely LEACH & EBCS. The data from table 4 were applied to compare the results of three algorithms for nodes in two different scenes. The parameter, called Epoch in neural network algorithm, is the number of algorithm learning stages or learning step. The value 1000 was specified by default. Another parameter to specify in simulation is the value of m number of nodes including max energy level applied as self-organizing neural network weight. This number is specified as a pilot and its values depend on the optimum number of clusters, which we expect to have. We surveyed the values in three different modes.

As figures 3-6 indicate, each cluster includes neighbor nodes in **LEACH** protocol and there is a boundary among clusters. The algorithm results indicate that each cluster does not include the required neighbor nodes and that it is a set of high and low energy nodes if the energy balance is maintained among all the clusters.

Table 3.Simulation parameters

Scene2	Scene1	Parameter
1000	**350**	**N**
Area	**۱۰۰*۱۰۰**	
Epoch	**۱۰۰۰**	
80	**۱۲۰-۱۰۰**	**۱۰۰-۸۰**
Initial Energy for one level clustering	**%۲۰**	
Transport Data	**%۱**	
Sence data	**%۱**	
Resive & Compact	**%۳**	
Pacet size	**Bits٤۰۰۰**	
Area	**%۲۰**	

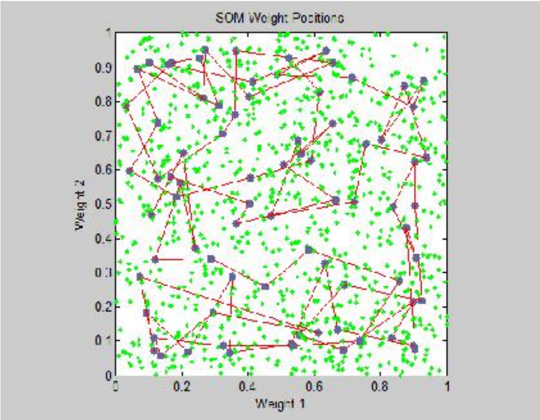

Figure 3. View cluster head node created in

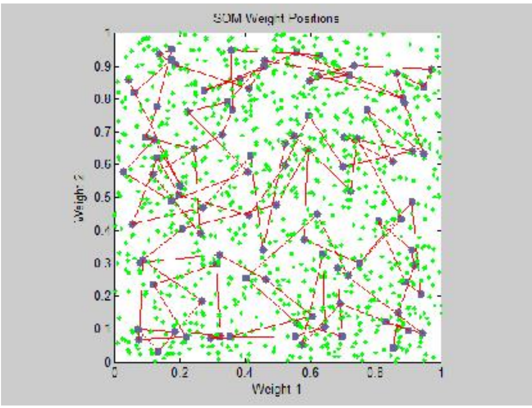

Figure 4. View cluster head node created 1000 by choosing M = 80
in 1000 by choosing M = 100

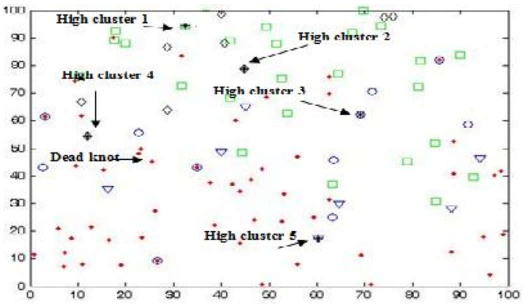

Figure 5. Cluster-heads: the results of

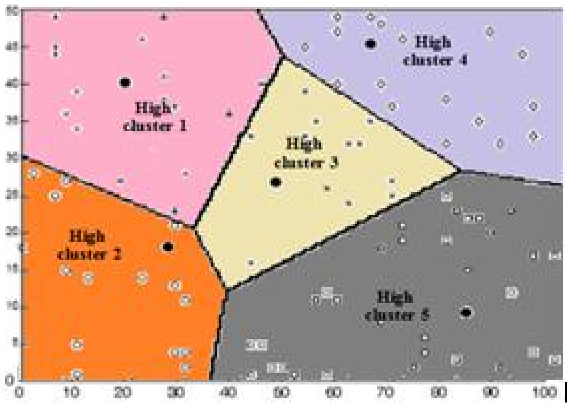

Figure 6. Cluster-heads: the results of
result of **SOM** algorithm
K-means algorithm

After we found out how the clusters are formed as a result of two different algorithms, we tried the proposed combinational algorithm to find out how the cluster-heads are formed. The results are presented below.

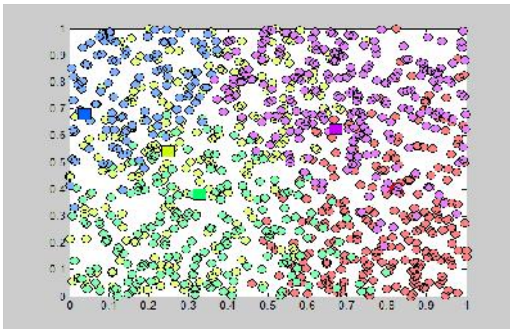

Figure 7. View of cluster-heads of

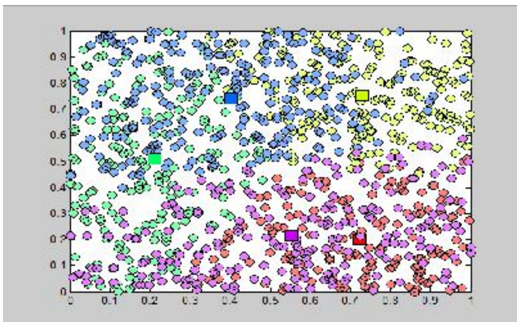

Figure 8. View of cluster-heads of 1000 nodes when M=80
1000 nodes when M=100

As we see in figures 9 and 10, the cluster dispersion level is obvious at the beginning of performing a new protocol. Then, as we move gradually forward through the protocol, after each step it tries to integrate and balance clusters to create integrated clusters.

The resutls of custering are presented in Figure 9 . The clusters integrated after 1000 steps. The input and output variables of each cluster are extracted from table1-4.

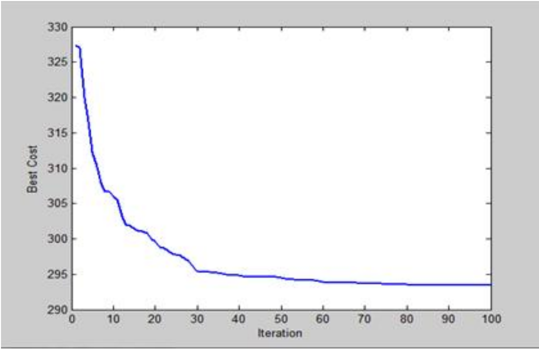

Figure 9. Integrated clusters

In the research, we used neural network to specify cluster-heads and their input and output energy level in wireless network of oil supply chain. Table 2 presents final findings

The above data are in percent and are multiplied by100 for a more exact estimate. We evaluated 33 neural networks clustered by SOM and K-means algorithm using CCR model in data envelopment analysis. It should be mentioned that the analyses are performed after data transmission.

We have defined at most 9 nodes as data sensors or member nodes of each cluster which direct the energy into the cluster and 1 node as cluster-head node which directs the energy out of the cluster. Then, we have used AP model to rank cluster-heads according to the degree of their efficiency..The cluster-heads with the score 1 are considered efficient ones. They can become model clusters for the others. Those with the score 0.4-1 are considered hopeful clusters and less than 0.4-inefficient. Efficient cluster-heads show the best performance in terms of energy consumption and have capability to continue working in ideal level. In addition, they can significantly improve the lifetime, constancy and monitoring of the network.

Inefficient cluster-heads can cause premature mortality of the network that is why their weak points should be removed. To do so, the inefficient clusters should be simply re-clustered by selecting another node as a cluster-head and using the proposed algorithm.

The results of the model are presented in the following table.

Table 4. Input and output of the model

	Input High cluster									Output High cluster
High cluster	Energy Units 1	Energy Units 2	Energy Units 3	Energy Units 4	Energy Units 5	Energy Units 6	Energy Units 7	Energy Units 8	Energy Units 9	Energy Output High cluster
١	220	151	90	95	54	121	59	123	270	329
٢	211	191	230	250	240	190	90	158	0	651
٣	320	325	228	241	148	147	139	197	201	985
٤	390	369	357	258	269	247	158	174	385	391
٥	220	210	241	20	36	125	125	126	185	296
٦	296	88	75	210	300	159	158	147	156	300
٧	420	390	169	185	226	0	0	0	0	543
٨	502	506	158	256	352	452	256	285	296	507
٩	125	185	169	258	295	248	456	852	752	874
١٠	259	358	154	175	189	99	20	420	489	579
١١	952	852	856	863	236	284	458	412	685	969
١٢	205	269	200	158	169	147	185	0	0	719
١٣	358	658	852	752	741	458	658	458	900	955
١٤	12	18	16	52	50	980	0	0	0	947
١٥	89	658	20	89	63	680	750	850	450	966
١٦	120	98	920	95	12	752	485	498	520	955
١٧	658	630	203	208	302	396	452	752	750	788
١٨	300	258	98	12	15	18	16	13	500	502
١٩	320	128	158	169	100	100	200	201	208	452
٢٠	800	748	750	485	320	520	451	499	666	806
٢١	102	85	900	854	458	659	632	320	899	1000
٢٢	198	520	758	632	20	289	641	0	0	645
٢٣	412	316	389	404	40	98	186	0	0	426
٢٤	70	205	209	368	0	0	0	0	0	541
٢٥	412	85	412	92	68	128	297	379	479	742
٢٦	700	250	0	0	0	0	0	0	0	832
٢٧	128	378	318	139	700	0	0	0	0	781
٢٨	212	189	585	740	950	222	789	850	860	887
٢٩	500	315	451	485	145	397	50	920	750	967
٣٠	205	96	38	158	174	123	0	0	0	980
٣١	658	854	754	358	751	726	0	0	0	996
٣٢	32	220	125	158	258	300	90	80	80	313
٣٣	758	789	741	752	654	258	456	420	320	827

The above data are in percent and are multiplied by100 for a more exact estimate. We evaluated 33 neural networks clustered by SOM and K-means algorithm using CCR model in data envelopment analysis. It should be mentioned that the analyses are performed after data transmission. We have defined at most 9 nodes as data sensors or member nodes of each cluster which direct the energy into the cluster and 1 node as cluster-head node which directs the energy out of the cluster. Then, we have used AP model to rank cluster-heads according to the degree of their efficiency..The cluster-heads with the score 1 are considered efficient ones. They can become model clusters for the others. Those with the score 0.4-1 are considered hopeful clusters and less than 0.4-inefficient. Efficient cluster-heads show the best performance in terms of energy consumption and have capability to continue working in ideal level. In addition, they can significantly improve the lifetime, constancy and monitoring of the network.

Inefficient cluster-heads can cause premature mortality of the network that is why their weak points should be removed. To do so, the inefficient clusters should be simply re-clustered by selecting another node as a cluster-head and using the proposed algorithm.

The results of the model are presented in the following table.

Table 5. Efficiency score and rank of the cluster-heads

Rank according to the model AP	Performance score	High cluster
22	0.518446	1
19	0.562486	2
12	0.818417	3
33	0.231679	4
16	0.633239	5
28	0.320779	6
15	0.637864	7
32	0.249445	8
10	0.967887	9
18	0.574135	10
29	0.310124	11
13	0.72975	12
24	0.38877	13
9	1	14
8	1	15
7	1	16
25	0.38527	17
6	1	18
21	0.531056	19
30	0.28	20
11	0.929126	21
23	0.499596	22
26	0.378	23
5	1	24
4	1	25
3	1	26
2	1	27
14	0.723741	28
20	0.555693	29
1	1	30
27	0.353297	31
17	0.618387	32
31	0.258902	33

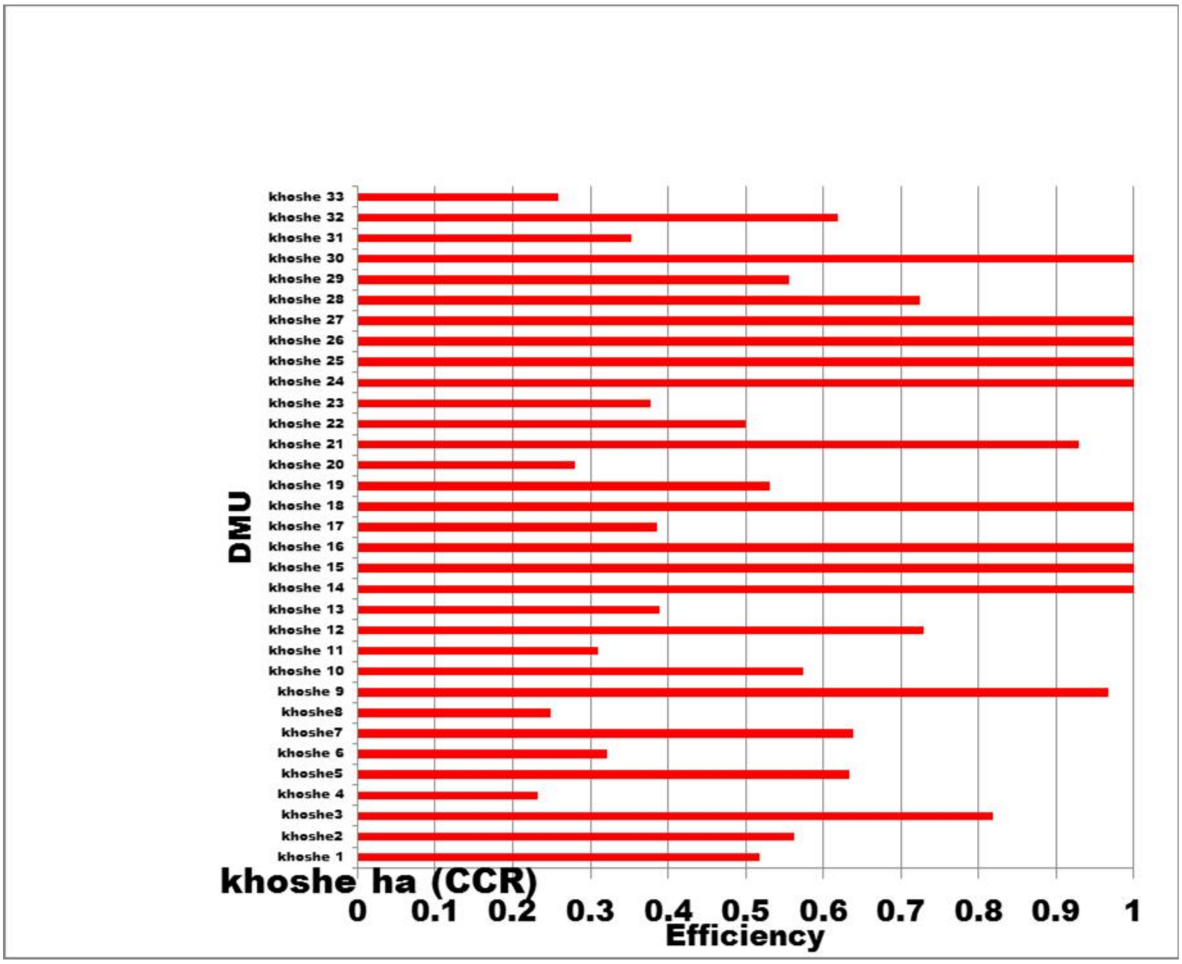

Figure 10. Graphic chart

Results and Suggestions

This study presented a combinational method based on neural networks and data envelopment analysis to improve the lifetime of strategic informational network. The studied network was an oil supply chain informational network. The results indicated that it is possible to evaluate the efficiency of the clusters and identify the sensitive and weak points of information distributers by identifying and clustering informational sensor nodes in supply chain network. Accordingly, it is possible to improve the network by the proposed approach and prevent it from wasting energy. The proposed model can be applied as an efficient tool in supply chain information network.

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