WIRELESS NETWORK CLUSTERING WITH GENETIC ALGORITHMS

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Abstract

Nowadays, network design and management can be considered well understood topics. Among the many innovations introduced in computer networks, an interesting issue is represented by wireless systems, which definitely change how networks are designed thanks to the absence of physical wires. In these new scenarios innovative and efficient management approach are needed and among them network clustering is absolutely the most important, for it heavily influences final performances. This paper describes a Genetic Algorithm based approach for wireless network clustering, suitable for the most common systems that can be found in modern factories such as WLANs and WSNs. Its aims are to optimize both traffic load between and within subnets and to take into account physical constrains which may arise because of radio transmission. The proposed technique can be adapted to very different requirements, as the experimental evaluation proves.

I. INTRODUCTION

Nowadays computer networks evolution is fast and new devices and standards become available almost every year. New technologies brings new devices and this makes old products out of date and therefore computer and communication systems must be constantly updated. Although technologic progress brings new capabilities and performance boosts, knowledge and design metodologies must be updated coherently to easily dominate the inherent complexity of these new systems.

Particularly in the factory automation field [7], computer networks design has been fulfilled with euristic methods based more on the designer's experience than on a sound theory. Network design and management was done more with a problem solving attitude than with a coherent strategy. Obviously this approach was not enough to manage large and complex systems, so new methods arose to successfully manage performance.

Among several techniques the most important surely is the network segmentation, that is the partition of all the hosts of a network in various subnets to optimize some global parameters. In literature many studies on the Network Division Problem are present [1]. These works are based on simulation or analytical study concerning a minimization study of a particular fitness function. These minimization studies take into account only a short range of parameters: this choice permits to reach only a partial and theoretical sub-optimal solution. On the other hand, by taking into account all needed network parameters the optimum itself could change. Genetic Algorithms represents a powerful techique for solving these problem and they have been extensively used to solve the partioning problem [2, 8].

Wireless networks are now widely used by users and even in factories these devices are more and more adopted. Therefore new issue must be addressed in network management, since wireless communication allows new solutions that could not be possible with wired systems, but on the other hand radio transmission causes new problems that can not be overlooked while designing a network.

This work presents a new clustering approach for wireless networks for factory automation based on Genetic Algorithms: in Sec. 2 the most common wireless technologies and systems are briefly presented, while in Sec. 3 a formal definition of the Network Division Problem is stated and analyzed. In Sec. 4 we present a new approach, based on a fitness function that may be adapted to the particular system in exam and in Sec. 5 we evaluate through experimental simulation how this method performs. Finally, in Sec. 6 some application and further improvements of this approach are explained.

II. WIRELESS NETWORKS FOR FACTORY AUTOMATION

Nowadays wireless networks are widely adopted because the absence of wires allow new solution and new design patterns that would have been impossible with old wired systems. These networks use low power radio waves, although some devices may use infrared or laser lights as well.

Wireless networks have experienced an impressive evolution and capillar diffusion among all field from consumer electronics to factory devices, especially due to the features they offer (low cost, easy installation, flexibility). On the other hand, wireless systems present also some negative issues, such as low reliability, easy installation and flexibility. The most adopted Wireless LANs protocols are *WiFi (IEEE 802.11), ZigBee (IEEE 802.15.4)* and *BlueTooth (IEEE 802.15.1):* these standards present different features and therefore are suitable for various operative conditions, since they differ both in offered bandwidth and devices' range. However, in the factory automation field Wireless LANs are not widely adopted, while Wireless Sensor Networks are the most common choice.

A **Wireless Sensor Network (WSN)** is a wireless network consisting of spatially distributed autonomous devices using sensors to cooperatively monitor physical or environmental conditions at different locations. Each node in a sensor network is typically equipped with a radio transceiver or other wireless communications device, a small microcontroller, and an energy source, usually a battery. The size of a single sensor node may vary and the cost of sensor nodes is similarly variable, ranging from hundreds of dollars to a few cents, depending on the size of the sensor network and the complexity required of individual sensor nodes. Size and cost constraints on sensor nodes result in corresponding constraints on resources such as energy, memory, computational speed and bandwidth. A WSN works with one or more sink stations, where all data are collected and processed. Usually these systems use the ZigBee protocol, which is particularly suitable for aforementioned requirements.

Even though their diffusion is seldom comparable to WSNs, **Wireless LANs** are also used to connect computers via radio waves, thus allowing single nodes to move and re-connect in a simple way. WLANs are based on the WiFi protocol and may use a distributed or a centralized architecture of communication.

III. NETWORK DIVISION PROBLEM

Network segmentation is the most powerful technique to design performant systems and in literature this issue has been treated as the Network Division Problem [2], where a network of several nodes must be divided in some subnets to minimize inter-subnets communication and thus improving global performances. This goal may be furtherly refined, including more design requirements in the problem statement.

The assignment of a node to a particular subnet is performed trough the analysis of the parameters of the network, the global traffic load, the particular functionality that a node presents; moreover some constraints are present due to the fact that some node are in a closer relationship with other ones, such as controllers and their direct sensors or nodes with realtime deadlines. Finally, some constraints may arise from the particular transmission technology or from the operative environment.

When the optimal configuration has been already found, this is suitable until new modifications are made to the systems or to the traffic load. This event is relatively rare in the factory automation field, since working systems may remain in use for long periods of time: consequently design techniques may spend more effort to find the best possible configuration, carefully optimizing even little details.

From a mathematical point of view, the NDP is a variant of the k-partition of a graph [4], which is a NP-problem: for a net with N nodes to be segmented in k different subnets k^N different configurations are possible, so there is a exponential explosion of the solution set and no suitable algorithm for an optimal solution can be found. Euristic methods are widely adopted to find an acceptable sub-optimal solution, so the NDP can be solved with a reasonable amount of time with a good approximation.

A good review about euristic method for NDP solution can be found in [4, 9], while other techniques based on genetic algorithms are presented in [3, 8]. A common element in all these approaches is the definition of a **fitness function** to estimate the quality of a given network segmentation given all the requirements: this functions evaluates to a number that expresses the ability of the particular segmentation to fulfill all requirements. An optimal solution for a heuristic method becomes a configuration that optimizes the fitness function.

Each configuration for a net with N nodes to be divided in k different subnets is represented as a N-dimensional vector, where each element contains the number of the subnet each node belongs to. This vector is the configuration vector and all possible configurations form the configuration set S, whose cardinality is exactly k^N. The fitness function is defined on S and it has real values: under this assumptions the segmentation problem can be restated as an optimization problem for the fitness function on the configuration set.

The analytical definition of the fitness function should contain all the network parameters, in order to compute an estimate of the quality of the configuration depending on these data and on the design goals. The desired goals are:

1. maximization of the traffic within each subnet;
2. minimization of the traffic between different subnets;
3. balance of the internal traffic in each subnet.

Apart from these standard requirements, more specific goals can be defined (realtime deadline on traffic, cost minimization of wires, etc). Wireless systems are particularly affected by the placement of nodes in the same subnets, for radio transmissions are strongly influenced by distance or mutual interference. Therefore additional goals must be stated:

4 minimization of spatial scattering for nodes in the same subnet;

5 maximization of distance between different

subnets.

These requirements must be analytically defined in the fitness function in order to obtain a value which truly represents a good estimate of the quality of a given configuration.

IV. A GENETIC ALGORITHM APPROACH

Genetic Algorithms [6, 5] are search techniques based upon the natural selection and survival of the fittest mechanisms. They have been applied successfully to a wide range of complex optimization problems to find exact or approximate solutions. Genetic algorithms are categorized as global search heuristics. Genetic algorithms are a particular class of evolutionary algorithms that use techniques inspired by evolutionary biology such as inheritance, mutation, selection and recombination.

Our approach uses genetic algorithms to solve the segmentation problem, so particular care should be taken on the definition of a suitable fitness function for the operative environment.

The application scenario presents several nodes to be connected, with point-to-point traffic: nodes are to be divided in subnets and each subnet contains a single point of access, thus creating several WLANs or WSNs independent from each other. All the access points can be further connected with a wired high bandwidth backbone. Wireless subnets are particularly suitable for factory environments, since often device cooperate because they are used in the same working cell.

Radio transmission presents some constrains on the segmentation process, since transmission range and possible interferences must be carefully handled, otherways subnets may suffer from poor signal-to-noise ration or several message collisions.

To sum things up, wireless systems present these design goals

1. maximization of the traffic within each subnet;
2. minimization of the traffic between different subnets;
3. balance of the internal traffic in each subnet;
4. minimization of spatial scattering for nodes in the same subnet;
5. maximization of distance between differetn subnets.

Fitness Function

The operative environment is represented as a square area of *lxl* m: *N* nodes are randomly placed on this area and they must be divided in *K* different subnets. Node *i* has coordinates (x_i, yi). The traffic between each pair of nodes is represented by a *traffic matrix T,* whose element *Tij* represents the traffic from node *i* to nodce *j,* expressed as ratio respect to the maximum bandwidth.

The first goal is to maximize intra-subnet traffic and minimize inter-subnet traffic. Let *L* be the *load matrix,* where the element *Lij* represents the traffic from all nodes in the subnet *i* to all nodes in the subnet *j:* therefore each element L_{kk} contains the traffic among all nodes in the subnet *k.*

A fitness function suitable for this first goal and which is maximal for best configurations is Eq. 1

$$f_1(X) = \sum_{i=1}^{K} L_{ii} - \alpha_I \sum_{i=1}^{K} \sum_{j=1, j\neq i}^{K} L_{ij}\,, \tag{1}$$

where first term represent intra-subnet traffic while the second one accounts for the inter-subnet traffic with a inter-subnet coefficient *αI.*

Fitness function in Eq. 1 does not require different subnets to have a similar amount of traffic load, so an optimal solution may group all node only in one subnet to obtain no inter-subnet traffic at all, thus making useless the segmentation. It becomes crucial to adequately balance loads of different subnets and the fitness function is modified to introduce this requirement:

$$f_2(X) = f_1(X) - \alpha_B \sum_{i-1}^{K} \sum_{j=1, j\neq i}^{K} \left| L_{ii} - L_{jj} \right|. \tag{2}$$

The new term in Eq. 2 evaluates how balanced are traffic loads of different subnets and it is weighted by a balancing coefficient α_B. This modification makes the configuration with only one subnet extremely unattractive, as well as other unbalanced segmentations, for the balancing term grows very fastly and therefore worsens the fitness function value.

A further refinement of the fitness function includes all constrains derived from the properties of wireless systems, essentially maximum transmission range and interferences between nodes belonging to different subnets. In order to achieve this goal spatial information about node displacement must be taken into account. For each configuration a *assignment matrix A* can be computed, where element *Aij* = 1 if node *i* belongs to subnet j while *Aij* = 0 if it's not. Center of mass (X_i, Y_i) for subnet *i* can be easily computed:

$$X_i = \frac{\sum_{j=i}^{N} A_{ij} x_j}{\sum_{j-i}^{N} A_{ij}} \qquad Y_i = \frac{\sum_{j-i}^{N} A_{ij} y_j}{\sum_{j=i}^{N} A_{ij}}. \tag{3}$$

Each center of mass represents an useful point to estimate how each subnet is placed with respect to other ones and how much nodes are far from the center of their own subnet. By using these data it becomes possible to furtherly refine the fitness function and adapt it to wireless networks:

$$f_3(X) = f_2(X) - \alpha_D \sum_{i=1}^{K} \sum_{j-1}^{N} A_{ij} \sqrt{\left(x_{ij} - X_i\right)^2 + \left(y_{ij} - Y_i\right)^2} \tag{4}$$

This new term evaluates the distance between each node and the center of mass of the subnet it belongs to: larger distances cause bad configuration fitness, since each subnet may suffer from unrealiable connections between nodes and higher power are required to guarantee successful transmission. This term is weighter by a dispersion coefficient α_D.

The last goal to achieve is to separate as much as possible different subnets in order to avoid mutual interferences: this requirement is easily defined with distances between the centers of mass of the subnets.

$$f_4(X) = f_3(X) + \alpha_S \sum_{i=1}^{K} \sum_{j=1}^{N} A_{ij} \sqrt{\left(X_i - X_j\right)^2 + \left(Y_i - Y_j\right)^2} \tag{5}$$

The additional term in Eq. 5 is higher when al subnets are clearly separated and not overlapping and it is weighted by the separation coefficient α_S.

Eq. 5 presents the final formulation of the fitness function, which includes all the goals aforementioned. This function depends, apart from the configuration, from the different coefficients used to weigh single terms: this parameters should be accurately tuned with simulations to improve the quality of this technique. While the first two parameters αI and α_B regulate traffic load distribution, the last two α_D and α_S are useful to regulate how much each configuration should optimize spatial distribution of subnets.

V. EXPERIMENTAL EVALUATION

In order to evaluate our fitness function the traffic matrix is randomly generated and each element contains a value between 0 and 100 but only with probability p. Two different scenarios are set up: in the low load scenario each pair of nodes exchange data only with probability $p = 0.25$, while in the high load scenario a value of $p = 0.9$ is used.

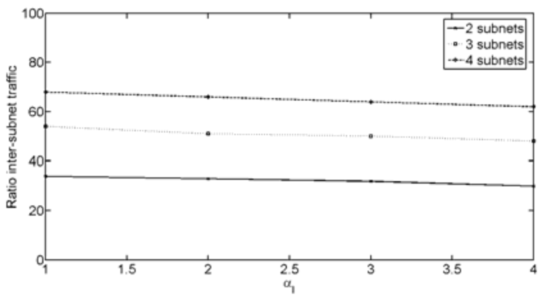

Fig. 1. Inter-subnet traffic minimization
with low traffic load

First of all we evaluated the fitness function only with the standard requirements of traffic load optimization, thus both α_D and α_S *are* equal to zero while α_B is constant and αI is changing. This paremeters strongly affects inter-subnet traffic load, which should be minimal.

In Figg. 1 and 2 the ratio of inter-subnet traffic load with respect to total traffic is shown as αI increases both for low and high traffic scenario: each scenario is segmented in 2, 3 or 4 different subnets. It appears clear that αi effectively influences traffic load between subnets, since as it grows this type of traffic dramatically shrinks. Furthermore a system segmented in more subnets performs worse, especially in the high traffic scenario, for segmentation can not separate nodes that intensively communicate anyway with each other. Finally, while in the low traffic scenario as αI grows the inter-subnet traffic becomes lower, in the high traffic scenario this is not true for the optimal segmentation has already been found.

In order to analyze how the coefficient of dispersion α_D affects the segmentation we choose values of $\alpha I = 3$ and $\alpha_B = 2$ obtained from previous analysis and then investigate how performances change when α_D grows. In this case we use the mean distance between nodes in the same subnets to evaluate the fitness function.

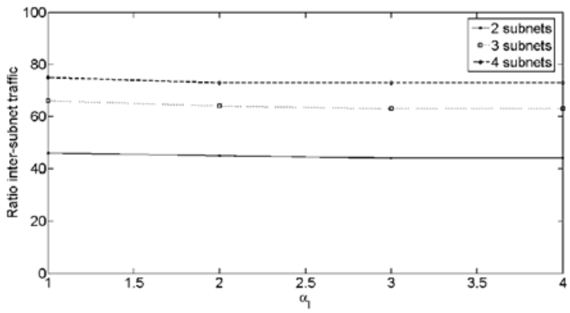

Fig. 2. Inter-subnet traffic minimization
with high traffic load

It is easy to note in Figg. 3 and 4 that α_D effectively regulates how much nodes within the same subnet are distant from each other: furthermore when the number of subnets increases the mean distance decreases since obviously in a subnet there are less nodes.

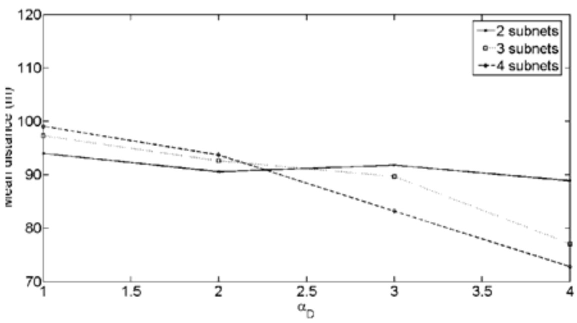

Fig. 3. Node distance minimization
with low traffic load

As in the previous case the high traffic scenario performs worse, probably since in the fitness function the inter-subnet traffic minimization term is so relevant that a good spatial optimization can not be found. On the other hand, in the low traffic scenario an interesting behaviour can be found: when only 2 subnets are created the mean distance is not affected by α_D because the optimal segmentation has already been found, while when 3 or 4 subnets are used the mean distance presents a dramatical decrease when the coefficient increases.

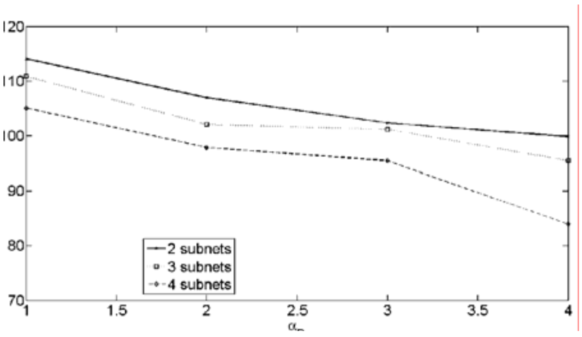

Fig. 4. Node distance minimization
with high traffic load

VI. CONCLUSIONS AND FUTURE WORKS

In this work we have presented a genetic algorithm based novel network segmentation technique for factory automation wireless systems. After a brief analysis of the constrains and the requirements of these systems we defined a suitable fitness function and then evaluated it through simulation and theoretical analysis.

New guidelines to improve and personalize the fitness function have been put forward, to adapt it to the specific systems to segment. Obtained results confirm the validity of this approach and further work may regard particular wireless protocol requirements or the analysis of segmentation with mobile nodes, which still represents an open field of research.

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