Learning Enhanced Situation Perception for Self-Managed Networks

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Abstract. The networks in the future it is envisaged that they will be able to operate in an autonomous manner. At the same time, the networks will be able to adapt their operation for handling new challenges. This thesis aims at providing a scheme for situation aware networking, based on a hierarchical architecture, which enables the network elements to operate in a self managed way taking into consideration the local and the greater (domain) view. In this thesis we propose a scheme based on fuzzy logic for the identification of optimization opportunities or problems, a functionality called situation perception. The proposed scheme has been applied and evaluated in three networking problems (i.e., identification of QoS degradation events' for VoIP, Load events' identification for WiFi APs, and Cooperative power control). Additionally, for handling the need for reconfiguration, in case of changes in the environment, we propose the enhancement of the situation perception mechanisms with two learning schemes (a supervised one and an unsupervised one). The enhancement is related to the adaptation of the environment modeling of the fuzzy reasoners. The proposed solution is described in a generic way so as to enable its application in other problems that have similar characteristics.

Keywords: autonomic networking, situation awareness, situation perception, fuzzy logic, supervised learning, unsupervised learning

1 Dissertation Summary

Moving towards future networks, the predictions indicate that mobile and wireless data traffic will increase considerably. Mobile data traffic will increase

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globally 13-fold between 2012 and 2017 whereas global IP traffic has increased more than fourfold in the past five years [1]. Additionally, a huge increase will take place regarding the number of the connected devices (100 billions). On the other hand, future networks will be more dynamic and complex compared to the contemporary ones, including new technologies, new services, and new demands from the users, new business cases. Thus, the network elements will have to be agile and dynamic so as to manage the users' networking needs and the network operational environment. In such a complex environment, where billions of diverse devices will (simultaneously) ask for resources from the network, networks' self-management aroused as a potential solution.

Additionally, we should consider that the future network conditions are hard to predict. This implies that the networks should be able configure their operation according to the new network stimuli, so as to handle unpredicted problems, optimization opportunities, and network conditions. For facilitating a network element to operate in the future demanding networks, a network element shall have the ability to monitor its environment, identify its state, make decisions, make projections, execute, and learn based on the previous actions. The literature analysis highlights an attempt of the self-aware schemes to mimic the human reasoning. However, due to their static definition of the environment, the schemes fail to meet requirement for human behavior approximation. Additionally, up to now both academia and industry attempt to handle the problem of environment modelling using rules and policies, combined with thresholds. Thus, we observe that a major gap of sophisticated solutions in the available proposals both in the literature and the industry solutions exists (i.e., mainly threshold based). In the following sections we present mechanisms developed in terms of this thesis for situation perception and awareness in future networks.

1.1 Fuzzy logic based situation perception

The term "Situation Perception" is used to describe all correlations that take place in order to analyze data received by monitoring points and thus identify problems and select appropriate configuration actions [2] [3]. This task is considered as a complex one due to its multi-variable nature since multiple optimization goals or faults may arise, the fact that contradictive inputs may occur, and since cases with missing data that may arise. These aspects may be handled using the Fuzzy Logic algorithmic tool (i.e., fuzzy sets enhanced with rules and policies). The Fuzzy Logic based situation perception, takes into account a set of metrics/parameters, and after their joint correlation analysis, maps them to a degree that depicts how the network elements perceives its environment (e.g., load status) [2].

A Fuzzy Logic Controller (FLC) consists of three parts, namely the fuzzifier, the inference system and the defuzzifier. The fuzzifier undertakes the transformation (fuzzification), of the input values (crisp values) to the degree that these values belong to a specific state (e.g., low, high). Then, the inference system correlates the inputs and the outputs using simple "IF...THEN..." rules. Each rule results to a certain degree for belonging to a specific state for every output. Thereinafter, the output degrees for all the rules of the inference phase are being aggregated. The actual output of the decision making process, comes from the defuzzification procedure, which captures the degree of the state of the decision maker (e.g., the network element is x% loaded; the radio link is y% interference, the user experiences z% QoS etc.). The degree is obtained using several defuzzification methods; the most popular is the centroid calculation, which returns the center of gravity of the degrees of the aggregated outputs.

1.2 Learning enhanced Fuzzy Logic Based Situation Perception

As mentioned afore, the Situation Perception schemes aim to identify problematic situations or optimization opportunities and in general perform well in the environments where they are built to operate. On the other hand, if the network conditions change/evolve, or the network elements get re-located in a totally new environment, they do not manage perform their situation perception task in a satisfactory manner, without being manually configured by the network administrators. Fuzzy logic enhanced situation perception faces the same problems regarding their adaptability as the rest of the situation perception schemes in the literature that lack inherent adaptability capabilities. In terms of this thesis two learning approach schemes are being proposed, one based on supervised learning and one on unsupervised learning. For the unsupervised learning scheme several variations of the solution have been proposed, depending on effect they have to the fuzzy logic reasoners.

1.2.1 Supervised Learning Algorithm

The supervised learning algorithm is a decentralized one, with parts of the algorithm being implemented locally in each network element and others being implemented in centralized controllers. Initially, each network element monitors its environment for identifying problematic situations using the Situation Perception fuzzy reasoners. In the case that problematic situations are being identified the network element proceeds in problem solving decisions and the corresponding execution of such decisions. Afterwards, the learning procedure takes place, which consists of three distinct phases, namely the labeling phase, the classification step, and, the fuzzy logic enhancement procedure [4] [5].

Each time a network device monitors its operational environment it extracts a d-dimensional vector which can be classified as True, indicating that a particular problem has appeared, False – no problem- or Medium/Neutral, implying that although there is currently no problem there is a chance that a problematic situation may appear in the future. Additionally, given a problem, the device triggers a remedy action, which is guaranteed to solve the problem; in other words it will enable the device to transit from a True state to either a False or a Neutral state. The correctly labelled observations are being used for the labelling of the rest of the observations, using kNN algorithm resulting in three sets, labelled as True, Neutral, and False, including all the gathered inputs, which may include misclassified observations. Thus a further step is required for ensuring that the misclassified tuples will be classified correctly. This is performed using k-Means, which is applied on the two spheres, corresponding to False and True and direct the algorithm to split it into two clusters, False or True and Neutral. The result will be two adjacent spheres maintaining elements belonging to both classes. The geometric representation of this approach is depicted in Fig. 1. The algorithm simply augments the sphere corresponding to Neutral cases and shrinks the other two by extracting falsely classified points. The intersecting points of the line defined by the spheres' centers with the spheres correspond to the desired solution, which straightforwardly leads to the identification of the input membership functions of the fuzzy logic controllers, as shown in bottom part of Fig. 1.

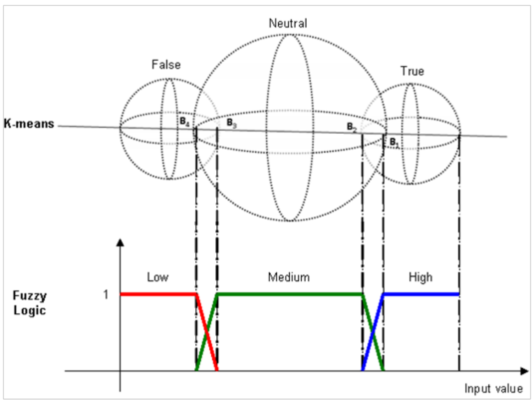

Fig. 1: Geometric interpretation of the approach

1.2.2 Unsupervised Learning Algorithm

The unsupervised version of the learning enhanced fuzzy logic situation perception scheme is based on the modification/adaptation of the previously described solution, following the same generic principles. The key difference of the unsupervised scheme lies at the skip of the complicated algorithm for labeling, following the assumption that the network administrator will have, in general, configured the network elements to operate adequately; thus enabling the system to converge. The previously described scheme exploits the measurements for the extraction of the new membership functions in a rather simple manner, using a well-known clustering method, the k-Means. This however leads to loss of information in the overlap areas of the clusters because the density of the measurements is not being consider, but only the radius of the hyperspheres is being exploited. In contrast, in the unsupervised learning scheme, the diversity of the input measurements via statistical analysis of the monitored instances is being considered [6].

Once we have gathered enough (classified) measurements we have three sets of tuples, labeled as Low, Medium and High; misclassified tuples of the diagnosis mechanism from the true negatives and false positives are also included in the three sets. The classification is based solely on the current understanding of the decision maker on what constitutes Low, Medium and High respectively. The approaches that we have followed regarding the statistical processing of the measurements are the use of the Gaussian distribution and, the non-parametric one (i.e., which uses the Kernel Density Estimator (Gaussian Kernel is used) of the measurements histogram). The former approach is simpler whereas the latter provides a better “fitting” to the available data. The mapping of both mechanisms to input membership functions is straightforward and is depicted in Fig. 2.

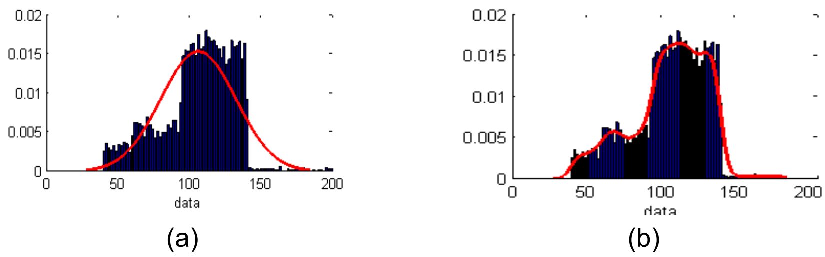

Fig. 2: (a) Mapping of a cluster to Membership functions using Gaussian statistical analysis, (b) Mapping of a cluster to Membership functions Non-parametric statistical analysis

2 Results and Discussion

The previously described proposals, for using fuzzy logic for situation perception problems, as well as the supervised and unsupervised learning enhanced fuzzy logic schemes have been applied in three case studies, namely QoS Degradation Events' Identification, Load events' identification, Environment modeling for Cooperative Power Control. The aim is to evaluate the mechanisms' efficiency for identifying appropriately events, as well as for adapting the model of the environment. In this section, the results of the application of the developed schemes are being briefly provided and analyzed.

2.1 QoS Degradation Events' Identification

For the QoS Degradation Events' Identification and for the VoIP service, delay, jitter and packet loss are identified as playing significant role in QoS degradation, thus the situation awareness engine is based on the aforementioned inputs for every active session; for other services (e.g., highly reliable communications, IPTV etc.) other monitoring inputs could be used. The "Delay", the "Jitter" and the "Packet Loss" per flow comprise the input vector, whereas the output is the "QoS degradation". The membership functions indicate the values of each parameter, the range of each value and the magnitude of their participation. The shapes chosen for the representation of the degree of certainty are trapezoidal in the case of "Packet Loss", mainly for simplicity reasons and to so as to exploit the certainty areas for such inputs and triangular for the jitter and the delay for highlighting the symmetry and the absence of total certainty areas. For the QoS level the Gaussian membership functions are being used. The idea behind such adoption is mainly based on the smooth (i.e., the QoS should be related to the inputs in a smooth manner without non-linear alterations) and non-zero (the decision maker needs to conclude to a decision based on all inputs' range) nature at all points; for simplicity reason symmetric membership functions are being used [6].

The evaluation of the fuzzy logic based situation awareness scheme for QoS degradation events is based on 50000 tuples that have been generated randomly, using typical values available in the literature [7]. For the analysis of the dataset, and given the huge number of the considered values, the dataset is being automatically evaluated against a set of predefined fuzzy logic rules, which are strict for the identified service. The extracted labels from now on will be called ground truth and are extracted using rules that perfectly fit to the considered dataset and are only used for the evaluation of the generic definition. Using the afore described initial configuration, the success rate is 64%, which represents the number that the situation awareness scheme concluded in the same decision compared to the ground truth.

In order to quantify the benefits from the introduction of the proposed learning schemes we have conducted a series of MATLAB simulations for the evaluation of the learning enhanced situation perception. Both algorithms have been applied for evaluating them and for identifying the benefits from their introduction. By applying the supervised learning algorithm (Section 1.2.1) the situation perception algorithm has a success rate of 70.01% (amelioration of

9.4%). By incorporating the unsupervised learning mechanism with the Gaussian adaptation approach and following the methodology presented in Section 1.2.2 we modify the input membership functions accordingly. As it is obvious, the input states are now being captured by new membership functions, which are being described by Gaussian distributions, with higher overlap areas. The success rate of the adapted scheme reaches 84.07% compared to the ground truth (an amelioration of 31.36%). The required time for the processing of the dataset and the extraction of the new membership functions is 13.07 seconds in an average consumer laptop (i.e., Quad core, 1.6 GHz, 4GB RAM). For the same dataset, we also apply the unsupervised learning non-parametric approach. The new membership functions are closer to the actual distribution of the dataset, and lead in reaching a success rate of 84.16% compared to the ground truth (an amelioration of 31.51%). In this case the required time for the adaptation procedure (processing and extraction of the new membership functions) is 22.38 seconds. The results of the analysis for the three learning schemes are being summarized in Fig. 3.

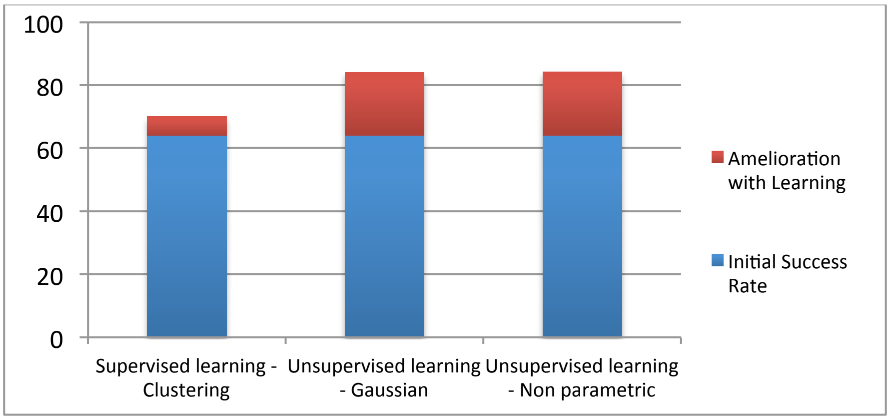

Fig. 3: Comparative analysis of the amelioration for the three learning schemes

2.2 Load Events Identification

The problem of load identification is under the coverage and capacity optimization umbrella. The analysis could be extended for any inference process that a network element should execute. In this use case, each AP monitors its operational environment (Packet Error Rate, Channel Utilization, and Number of Associated Terminals) and attempts to identify potential (high) load situations [4] [5]. If such a problem occurs (high load) then they collaborate in order to select the most appropriate configuration action, which in this case is the optimal reallocation of the associated terminals among the available homogeneous or heterogeneous access points in the corresponding network area; the UEs reallocation has been extensively studied in the literature and is out of the scope of this analysis.

The shape of the membership functions (MF) is related to their special characteristics. More specifically, for the AT the MFs are trapezoidal. The key characteristic of this MF is its simplicity and is mainly used to describe inputs that have a homogeneity degree and linear behaviour. Similarly, for the strict nature of the PER and its relation to the QoS we have decided to use the trapezoidal MFs, which describe in a satisfactory manner the considered error ranges for ideal ("low"), acceptable ("medium") and non acceptable ("high"). Finally, the triangular MFs have been selected for the "Channel Utilization" parameter due to the linear affect of this input to a WiFi AP. In order to test the effectiveness of the proposed solution we have used three initial configurations of the fuzzy logic decision-making controller so as to capture more generic and more targeted configurations of the network equipment.

The evaluation of the proposed scheme is based on an experimental analysis for generating an evaluation dataset. This testbed was employed in order to extract the dataset used in the experimental assessment. We collected 50.000 tuples; each tuple was described by three variables indicating the status of an access point at time t_x, namely Packet Error Rate (PER) ranging in [0…1], Channel Utilization (CU) ranging in [0…1] and Number of Associated Terminals (AT) in [0…25] [8]. 10% of the dataset has been sampled from the deployment of the testbed and has been manually labeled, while the rest has been artificially generated.

The basis of the analysis is a pre-evaluation of the dataset, with a very strict set of rules, directly capturing the environment where the APs are placed. The evaluated dataset is called ground truth and is used only for evaluation purposes. Evaluated against this dataset, all the three fuzzy logic controllers' configurations performed well, considering ofcourse the fact that they have been generally configured. **Table 1** presents the success rate (i.e., the correctly classified tuples) using the three different configurations. We observe that the more generic a configuration is, the lower success rate he achieves, which is understandable due to the fact that the configurations matches several environments.

Table 1: Classification success rate results for the three configurations of the fuzzy reasoners

Configuration	Fuzzy Logic 1	Fuzzy Logic 2	Fuzzy Logic 3
Classification Success Rate	65.64%	71.86%	75.40%

For the load events' identification case, the supervised learning scheme has been applied for the identification of load events. For identifying the optimum value of neighbors for the kNN algorithm, we have performed several experiments with values of k 1, 5, and 10. The results have been assessed through a 10-fold cross validation procedure, while all experiments verified our initial intuition regarding the applicability of k-NN in the context of our problem exhibiting, a classification rate larger than 98%. The latter lead us to the additional conclusion that any value between 1 and 10 will provide results of adequate quality.

Based on the experiments we conclude that the algorithm performs significantly well and tends to provide environment modelling, which converge to decisions closer to the ground truth, independently of the initial configuration of the network element's decision making engine. For the three initial configurations of the fuzzy logic controller the achieved amelioration is of 14 - 17% (**Table 2** - Fig. 4). The presented amelioration focuses on the situation awareness of a cognitive manager. The characterization of events, which is a situation awareness phase, is the pilot for the successful optimization or fix of the network system. If the cognitive manager cannot assess effectively the local status, then the performance of the network in many cases will not be improved by applying a reconfiguration action. Thus, the correct labeling of events is an important task for autonomic network management systems, where the learning process has merit.

Table 2: Classification results after the enhancement of the fuzzy logic rules

	Fuzzy Logic 1	Fuzzy Logic 2	Fuzzy Logic 3
Initial	65.64%	71.86%	75.40%
Learning	76.73%	84.09%	86.06%
Amelioration	16.8%	17.01%	14.13%

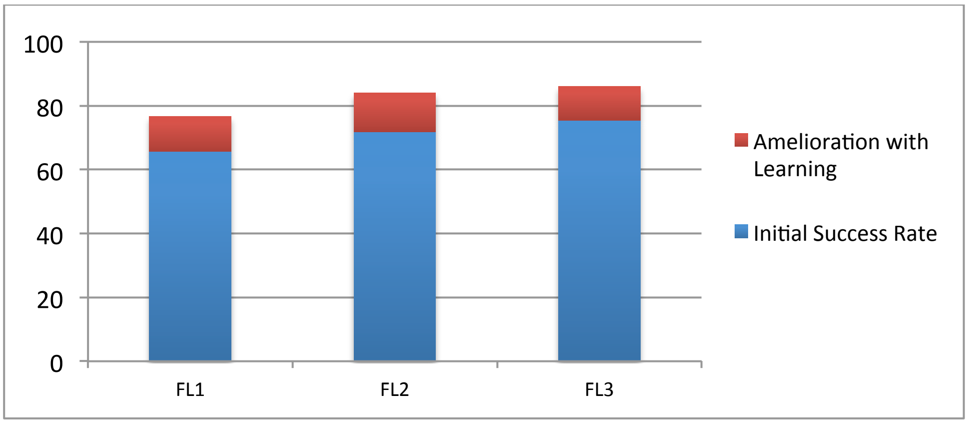

Fig. 4: Comparative analysis of the amelioration for the three initial configurations

2.3 Fuzzy Logic-based Cooperative Power Control

This section aims at presenting a Situation Perception mechanism for WiFi APs operating in an Ultra Dense Environment, where uncertainties may occur. The idea is to extend algorithms for cooperative power control coming from sensor networks' application field [9] [10], apply the solution in WiFi APs, and address the situation perception problem due to uncertainties that may occur in the network.

Both of the algorithms presented in [9] and [10] are based on a tradeoff between the capacity of a node and the interference caused to the corresponding neighborhood. This balance is being captured by an objective function of the following type [9]:

$$A+\alpha B \quad (1)$$

The first part indicates a relation to the Shannon capacity for the corresponding user, while the second part captures the negative impact in terms of interference prices that a user causes to its neighborhood. The α factor is introduced so as to capture uncertainties in the network; these uncertainties reflect the precision of the received and compiled information of each network element regarding the interference price, which should have been available by the node's neighbors. This is related to the fact that once a network element adjusts its transmission power, it informs its neighbors in an ad-hoc manner. This implies that even though a network element has collected information from all of its neighbors in order to adjust its transmission, the gathered data could be obsolete and, as a consequence, they will not capture neighborhood's current state. In [9], *α* is set in a static manner as 25%. In [10], a fuzzy reasoner is introduced in order to identify, in a more dynamic way, uncertainties in the network based on the network's status; the inputs (number of users, mobility, update interval) of the fuzzy reasoner capture the volatile nature of the ad-hoc network, whereas the output of the fuzzy reasoner is the Interference Weight. The α factor is defined as 1/β Interference Weight + 1 (β has the maximum value of the Interference Weight). In our proposed scheme [11] [12] [13], we suggest using fuzzy logic controllers for the calculation of the *α,* which afterwards shall be adapted, based on the introduction of the learning schemes.

The evaluation of the fuzzy logic enhanced scheme is based on a full day experiment [12]. In the experiment four Soekris APs have been operating enhanced with the developed solution; the transmission power of their WiFi cards is being measured throughout the experiment. The transmission power of the WiFi APs ranges from 10 to 27 dBm. For each of the Soekris devices (and considering that the 10dBm is the basis of the TxPower for each AP) we have measured the actual gain compared to setting the transmission power to the maximum TxPower (i.e., 27 dBm). The energy gain at each of APs is 12.51%, 10.75%, 33.33% and 21.23%. Also, the analysis showed that the more the APs, the more energy gains we have, due to the collaborative nature of the algorithm. Also, what should be noticed is the fact that the APs change very often their TxPower levels. This is related to the highly volatile office environment, with moving users and the many interference sources (i.e., moving users, cell phones, Bluetooth devices, etc.), in relation to the fact that the APs identify the network topology considering indoor path loss models. Such models, if we assume static environments, without moving users operate with accuracy, however in the case under discussion, the network elements need to calculate the topology on a constant basis, in every CPC loop. Throughout the experiment the SINR has been being measured and it is better compared to the case where maximum TxPower has been set to the APs. Additionally, we have been measuring the number of iterations required for the system to converge, every time the CPC is being triggered (every 5 minutes). The Soekris APs exchange messages asynchronously; everyone using its own intervals.

We observe that the scheme converges in small number of iterations most of the times (mean value of iterations 3.876).

A similar analysis has been performed when we integrated the supervised learning scheme [12]. The initial configuration of the network elements is a generic one and captures a great variety of environments. The CPC scheme is more sensitive to the environment, compared to the second day of experimentations (CPC without learning), due to the increased number of fluctuations in the TxPower setting. Given the fact that they operate in the same environment, the APs proceed even more often in transmission power adjustments. Furthermore, we observe significant energy gains, in relation to the case without learning capabilities (24.73%, 18.01%, 14.69%, 5.65% energy gains). Regarding the SINR, it remains in the same levels as in the case of the core CPC algorithm due to the fact that the objective function to be optimized is the same. The number of iterations every time the CPC is being triggered after the learning procedure slightly decreases (3.47), which also highlights that the system has become more suitable to its environment.

3 Conclusions

The objective of this thesis is to analyze the concepts of the Situation Awareness and Situation Perception and present solutions for these research areas. Situation Awareness is the ability of the network elements to model their environment, assess it and interpret it so as to predict the near future. As situation perception we define the proper perception of the operational status of the system or the network element and is the primarily interpretation of the available information. In the context of this thesis, the focus has been placed on the analysis of the previous notions, and on the development of an architectural solution that enables network elements to perceive their environment correctly and efficiently. Additionally, new schemes for efficient and effective situation perception based on fuzzy logic have been proposed. These schemes have been enhanced by adaptation-learning mechanisms, so as to be able to adapt their contextual models, based on the environment stimuli. The evaluation of the proposed schemes has proven that fuzzy logic schemes for Situation Perception perform well for the environment modelling. Additionally, the developed learning schemes adapt the environment modelling and benefit significantly the performance of the Situation Perception schemes.

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