IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 12, No. 2, June 2023, pp. 648~655
ISSN: 2252-8938, DOI: 10.11591/ijai.v12.i2.pp648-655

New approach for selecting multi-point relays in the optimized link state routing protocol using self organizing map artificial neural network: OLSR-SOM

Omar Barki, Zouhair Guennoun, Adnane Addaim
Research Team in Smart Communications, E3S Research Center, EMI, Mohammed V University in Rabat, Rabat, Morocco

Article Info

Article history:

Received Jul 29, 2021
Revised Oct 1, 2022
Accepted Oct 31, 2022

Keywords:

MANET
MPR
OLSR
SOM

ABSTRACT

In order to improve the selection of multi-point relays (MPRs) by a node node performing the computation (NPC) in the optimized link state routing (OLSR) protocol and therefore to guarantee more security for the routing in the mobile ad hoc network (MANET), we propose new approach that could distinguish between the strong and weak MPRs in the list of MPRs already selected using the standard algorithm described in RFC3626 document. This approach is based on self organizing map (SOM) artificial neural network that processes the collected data and then only selects the strong MPRs using a set of criteria allowing a reliable retransmission and a strong link and therefore better network performances. The obtained results, from the simulations that have been carried out using a customized network simulator 3 (NS3) network simulator, show an improvement in terms of throughput, packets delivery ratio (PDR) and the security of the network compared to the standard approach.

Corresponding Author:

Omar Barki
Research Team in Smart Communications (ERSC), Engineering Mohammadia School
Mohammed V University in Rabat
Avenue Ibn Sina BP765 Agdal, Rabat, Morocco
Email: omarbarki@research.emi.ac.ma, obarkiomar@gmail.com

1. INTRODUCTION

The selection of multi-point relays (MPRs) nodes according to the algorithm described in requests for comments3626 (RFC3626) document [1] is limited to symmetrical connections between nodes. This issue generates several drawbacks in practice on the ground, especially with other parameters that must be integrated into the calculation of these MPRs, namely the nodes energy, the nodes mobility, the nodes geographical position and the bandwidth link between nodes.

In the literature, many researches have tried to develop the selection of MPRs in the optimized link state routing (OLSR) protocol by proposing new approaches [2]. In order to improve both quality and security in selection of MPRs the researchers used several techniques. There are those who treated just the energetic side of the nodes [3]–[7] others treated the effect of mobility [8]–[12]. To integrate more parameters both in the calculation of MPRs and in order to improve the functioning of mobile ad hoc network (MANET) networks precisely of the OLSR protocol, the researchers used techniques (genetic algorithms and neural networks) making it possible to process and combine several criteria at the same time, but, they still remain less efficient because they only integrate some parameters and not all.

The important role that neural networks play in processing and analyzing data for the purpose of classification or prediction has prompted us to conduct a study on a set of approaches [13] which summarizes the use of neural networks in MANETs. Some researchers have focused their study on the use of artificial neural network (ANN) for the detection of anomalies and attacks in the network [14], [15] and some for the mobility prediction [16]–[18] and the others for optimization of the route from source to destination and traffic estimation [19]–[21]. This study has shown that the different ANN offer a great capacity for modeling [22], [23], classification [24], [25] and prediction [26] of future values on the basis of data collected over time for a given event. In the next section, we will describe the principle of our new approach that uses self organizing map (SOM) ANN classification technique to improve both quality and security in MANET. Finally, in section 3, we will present the simulations that we carried out and then we will present their results and discution.

2. NEW APPROACH FOR SELECTING MPRS: OLSR-SOM

2.1. Our approach description

Our approach is based on the artificial neural network of SOM classification which allows sorting the MPRs nodes into distinct groups based on data extracted as the simulation progresses. The groups formed are subjected to a filter of criteria that we have defined to determine the strong and weak classes. The MPRs that is belonging to the weak class will be eliminated from the final list of MPRs used later in routing by OLSR protocol under NS3, and so on until the end of the simulation.

This new OLSR-SOM approach is based on the following steps:

– Fix a given NPC node named X
– Collect from a trace file for a duration time (dt) the information on all the MPRs selected by the standard OLSR algorithm executed by the node X and save them in a Fdata file as a learning database for SOM
– From a time (t>dt), we collect the data of the 1st list of MPRs selected by the node X (Lmprs) (considered as MPR condidates) and put them in a Fdata_mpr file
– Submit Fdata and Fdata_mpr to SOM under Scilab to classify the MPRs and determine the class of each MPR in Lmprs
– Determine the criteria of the weak MPRs class to delete named C_supp
– The MPRs of Lmprs belonging to C_supp are deleted from the Lmps list to obtain a new definitive list LmprsDef with which we continue the simulation
– We complete Fdata by Fdatampr which is used to learn the future list of mprs of node X This procedure is repeated for each MPRs list of the node X during the simulation.

The data collected for each MPR:

Energy: the energy remaining at the time t of this MPR.
Distance: Distance between MPR and NPC at the time t.
Tx (NPC): number of packets sent by NPC to MPR at the time t.
Rx (mpr): number of packets received by MPR from NPC at the time t.
DurationL: duration between Tx and Rx.
ThroughputL: link throughput = Rx/durationL.
PDRL: The link packet delivery rate = Rx/Tx.

2.2. OLSR-SOM scheme

The improvement made on OLSR to obtain OLSR-SOM focuses on filtering and reducing the list of MPRs already selected by standard OLSR algorithm presented in Figure 1(a) to a new list of MPRs considered strong to ensure the transmission of the messages and data with high reliablity as shown in Appendix. The changes made to OLSR to get OLSR-SOM are shown the Figure 1(b) as shown in appendix. In Figure 1(b), we have added classification processing on the list of MPRs (already selected by the standard MPRs selection algorithm described in RFC3626) using the SOM ANN in Scilab software for the classification followed by the selection of a new list of MPRs for the node X.

3. RESULTS AND DISCUSSION

In order to prove the effectiveness of the new OLSR-SOM MPRs selection approach in terms of quality and security, we have run several simulations using NS3 which is an open source discrete event simulation tool. To support our OLSR-SOM MPRs selection approach, we modified the MPRs selection algorithm included in NS-3. These simulations have been carried out to study two cases. The first one is related to evaluate the perfomace measures of the MANET network using this new OLSR-SOM MPRs selection approach and the second one is concerning the performance evaluation of the MANET network against the distributed denial of service attack (DDOS).

3.1. Perfomace evaluation of the MANET network using a new OLSR-SOM approach

In order to evaluate the performance of the new OLSR-SOM MPRs selection approach. We consider the following scenario in which the number of network nodes is fixed whereas the number of nodes implemented the new OLSR-SOM algrorithm is increasing. The simulation parameters are given in Table 1.

We run several simulations in order to evaluate some measures of the performance of the MANET network; namely the packet delivery rate (PDR), the throughput, the packet loss and the energy consumption, by increasing the number of OLSR-SOM nodes from 1 to 5 in the network of 10 nodes as indicated in the Table 1. We plot the simulations results in Figures 2-5 representing the evolution over time of the PDR, the troughput, the packet loss and the energy consumption respectively. According to the Figure 2, we note that the PDR parameter at the beginning of the simulation has the same value for the different cases. But after 40 seconds of execution the PDR increases proportionally to the increase in the number of OLSR-SOM represented by OLSR-SOM1, OLSR-SOM2, OLSR-SOM3, OLSR-SOM4 and OLSR-SOM5. This latter shows a significant increase over the standard OLSR hence the OLSR-SOM is better than the OLSR-standard regarding the PDR parameter.

The Figure 3 shows that that the average throughput in the MANET network at the beginning of the simulation has the same value for the different cases and that during the learning step of the SOM neural network. After around 40 seconds of execution that the average throughput becomes increasingly important by increasing the number of OLSR-SOM nodes. the figure also shows that the curves of the different cases of OLSR-SOM during the simulation time show higher values compared to the OLSR standard.

In the Figure 4, we note that the simulation from 0 second to about 50 second. The loss of packets has the same value for all the cases but from 60 to 135 second the loss of packets for standard OLSR begins to increase and exceeds the curves of OlSR-SOM at beyond 135 seconds. The decrease in packet loss is relevant when comparing the new approach in particular "OLSR-SOM5" against the standard OLSR.

Table 1. Simulation parameters for the first scenario using the NS3 simulator

Parameters	Values
Number of nodes in the network	10
Number of OLSR-SOM nodes	From 1 to 5
Simulation time	160 seconds
Mobility model	RandomWayPoint
Initial energy of each node	150 J

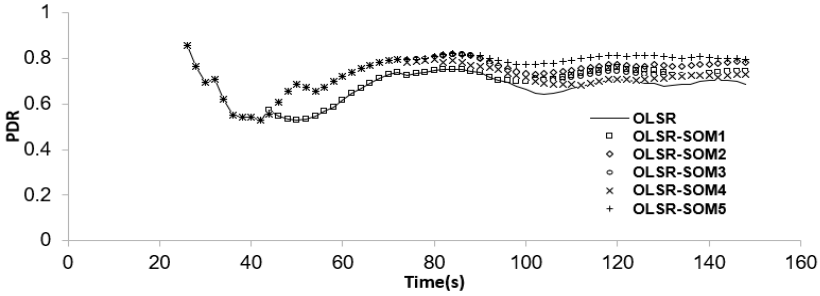


Figure 2. Evolution of PDR per time

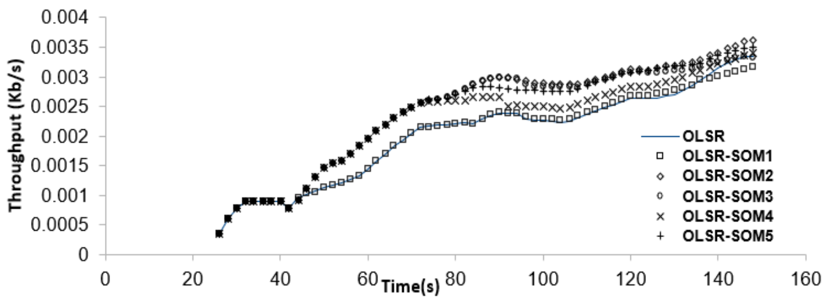


Figure 3. Evolution of throughput per time

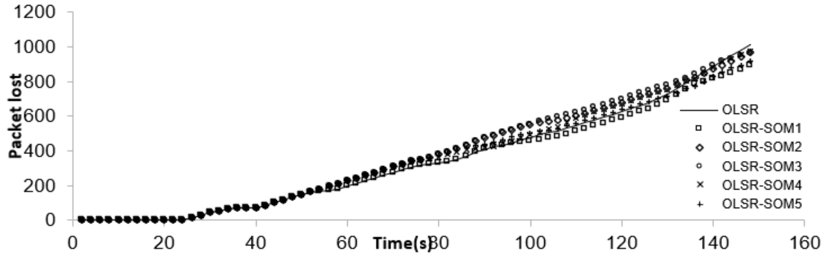


Figure 4. Evolution of packet lost per time

According to Figure 5, during the simulation from start to finish, the values colleced for the energy consumption are almost the same for all cases. The comparison of energy consumption in the MANET network of the different cases of OLSR-SOM against the standard OLSR shows a slight difference between the standard algorithm and our approach. Thus, it can be said that OLSR-SOM remains stable in terms of energy consumption.

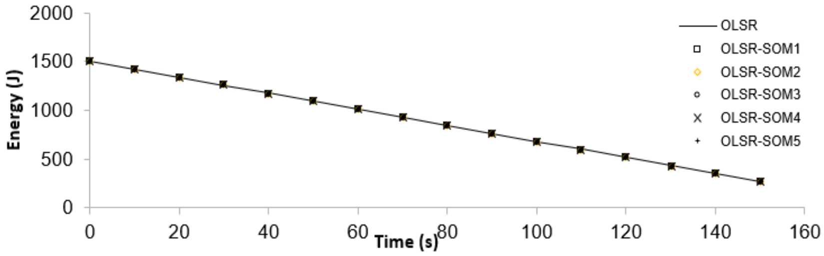


Figure 5. Evolution of energy consumption per time

3.2. Performance evaluation of OLSR-SOM against the DDOS attack

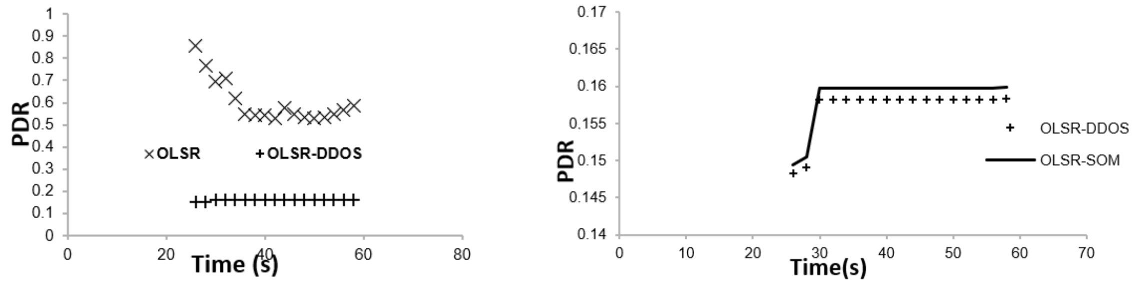
In order to evaluate the performance of the new OLSR-SOM MPRs selection approach against the DDoS attack, we consider the following scenario in which we applied OLSR-SOM on all nodes in the network with the presence of a DDOS attack launched by a given node. The simulation parameters are given in Table 2 and the obtained results are presented in Figures 6-9.

Table 2. Simulation parameters for the second scenario using the NS3 simulator

Parameters	Values
Number of nodes in the network	10
Number of OLSR-SOM nodes	10
Simulation time	60 seconds
Mobility model	RandomWayPoint
Initial energy of each node	150 J

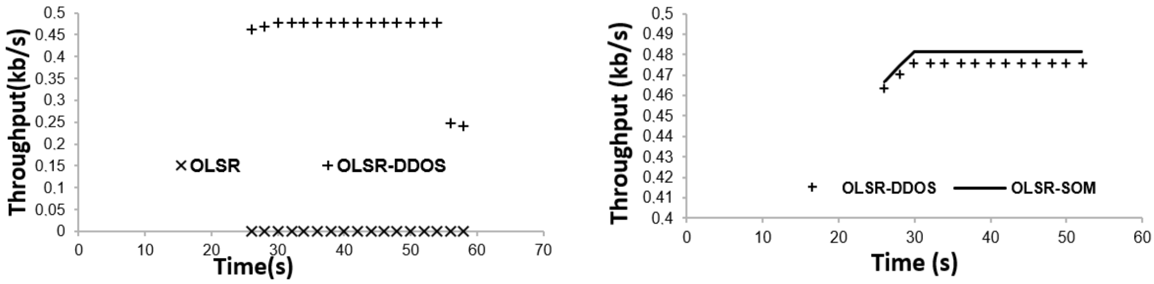
In this second scenario, we applied OLSR-SOM on all nodes in the network with the presence of a DDOS attack launched by a given node. The obtained results are presented in Figures 6-9. On the one hand, the evolution of the PDR parameter for the OLSR standard compared to OLSR-DDOS illustrated in Figure 6(a), shows that the injection of DDOS attack into the network significantly reduced the PDR compared to standard OLSR. On the other hand, the evolution of PDR for OLSR-SOM compared to OLSR-DDOS illustrated in Figure 6(b) shows that OLSR-SOM increased the PDR compared to OLSR-DDOS by discarding nodes overloaded by DDOS and using the less overloaded MPR nodes to transmit messages in the network. So, the new approach also reacts against attacks to select the not overloaded MPR.

The evolution of the throughput parameter for the OLSR standard compared to OLSR-DDOS illustrated in Figure 7(a), shows that the DDOS attack overloading the network and blocking the functioning of the standard OLSR hence the low value of throughput parameter. However, the evolution of the throughput parameter for the OLSR-SOM compared to OLSR-DDOS illustrated in Figure 7(b) shows that the OLSR-SOM gives better throughput than OLSR-DDOS.



(a) (b)

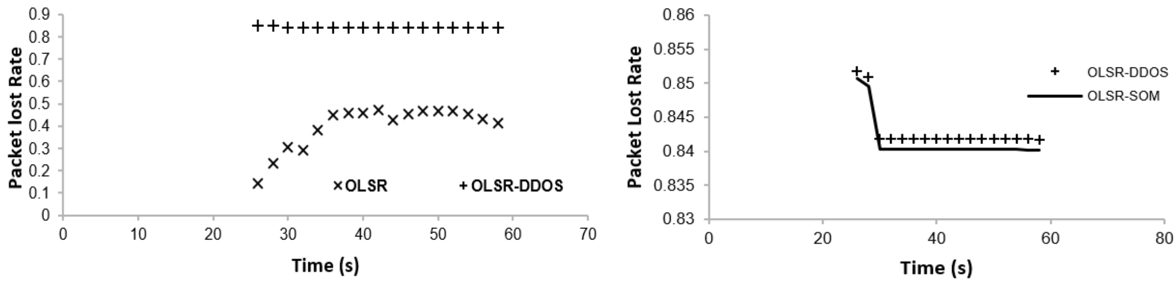
Figure 6. Evolution of PDR per time for, (a) OLSR compared to OLSR-DDOS and (b) OLSR-SOM compared to OLSR-DDOS



(a) (b)

Figure 7. Evolution of throughput per time for (a) OLSR compared to OLSR-DDOS and (b) OLSR-SOM compared to OLSR-DDOS

The evolution of packet loss rate parameter for the OLSR standard compared to OLSR-DDOS illustrated in Figure 8(a), shows that the flooding created by DDOS attack at the network level has blocked the transmission of packets and therefore a very high packet loss rate. However, we notice that the evolution of packet loss rate parameter for the OLSR-SOM compared to OLSR-DDOS illustrated in Figure 8(b) shows that the OLSR-SOM has reduced this rate by avoiding the selection of weak MPRs.



(a) (b)

Figure 8. Evolution of packet lost rate per time for (a) OLSR compared to OLSR-DDOS and (b) OLSR-SOM compared to OLSR-DDOS

Concerning the evolution of the energy consumption parameter, the Figure 9 shows a similarity between the values given by the curves of the different protocols studied, namely OLSR, OLSR-DDOS and OLSR-SOM. The difference between them is that the OLSR-SOM compared to OLSR standard and OLSR-DDOS protocol has presented an importants results for the other parameters (PDR, throughputs and packet loss). in contrary, the OLSR-DDOS is an attack that causing the bad values for PDR, throughputs and packet loss parameters hence the important role of our new approach.

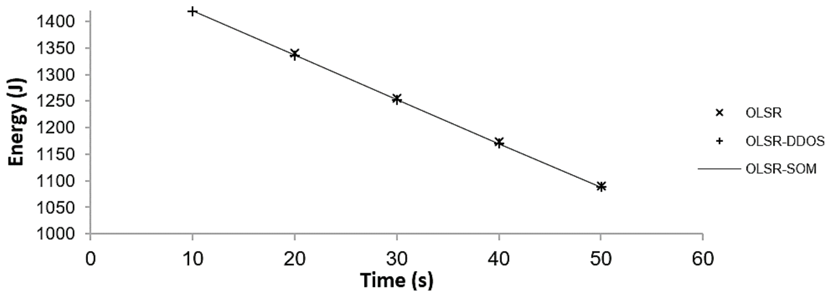


Figure 9. Evolution of energy consumption per time

4. CONCLUSION

In this article, we have tried to improve both the quality and the security of the OLSR protocol and precisely the method of selecting MPRs nodes. To achieve this goal, we have integrated several parameters in the calculation of the MPRs noeds using the artificial neural network approach called SOM which makes it possible to classify the collected data into a defined number of classes, the application of a filter on these classes will make it possible to determine the strong and weak MPRs nodes and therefore the use of the strong MPRs in a final list in routing process. The obtained results from series of simulations using NS3 platform has proved the high performance of OLSR-SOM approach compared to standard OLSR in terms of both quality and security, especially with the observed increase in the throughput and the PDR, and with the decrease in the packet loss, whereas the energy consumption has kept the same level.

APPENDIX

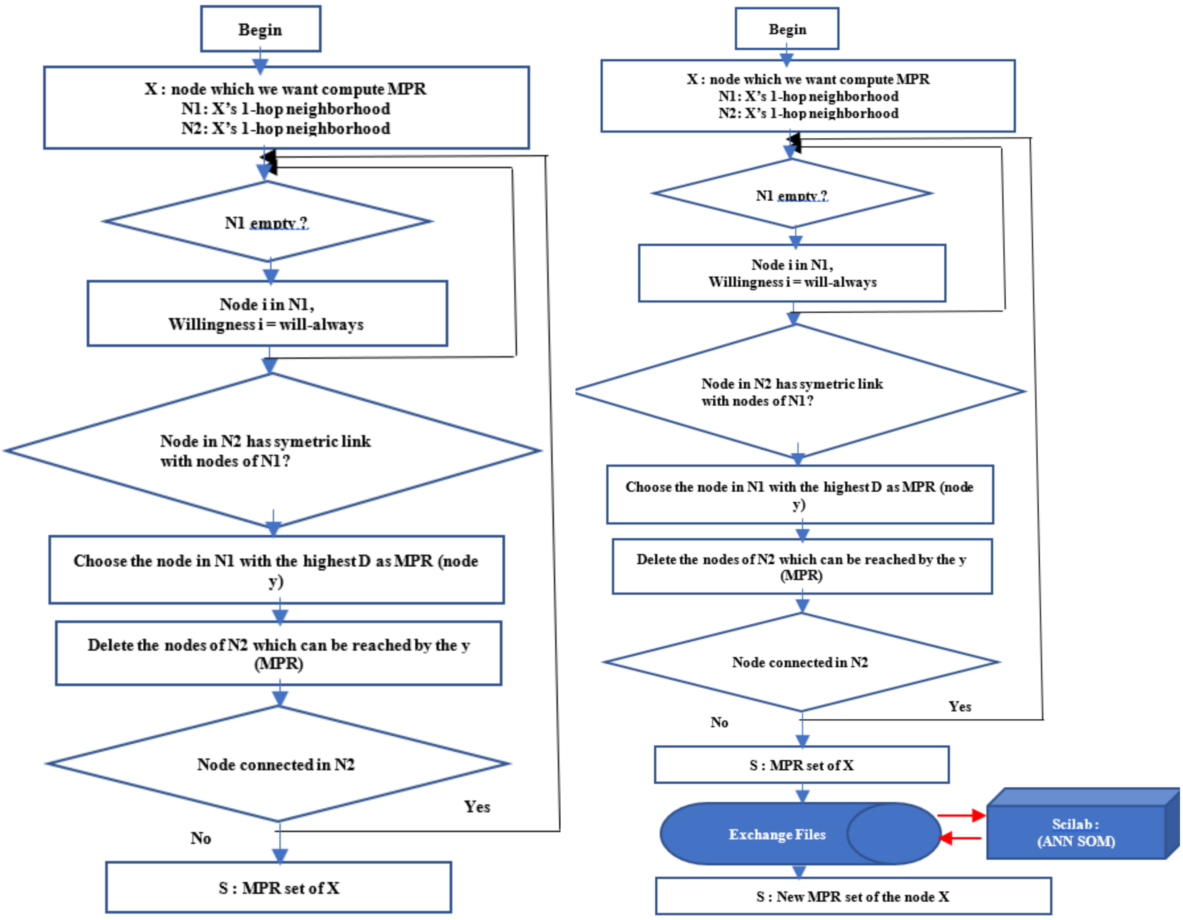


Figure 1. MPRs selection algorithm, (a) Standard OLSR and (b) OLSR-SOM

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BIOGRAPHIES OF AUTHORS

Omar Barki PhD student in Research Team in Smart Communications-ERSC, E3S Research Center, EMI, Mohammed V University in Rabat, Morocco. He was born in ERRACHIDIA, Morocco in 1975. He received his MST degree in Software Engineering in Sciences and technologies Faculty in 1998, and his Advanced graduate degree in informatics and Telecommunications from Faculty of Sciences of Rabat in 2008, His fields of interest are networks architecture and wireless sensor network. He can be contacted at email: obarkiomar@gmail.com.

Zouhair Guennoun Research Team in Smart Communications-ERSC, E3S Research Center, EMI, Mohammed V University in Rabat, Morocco. Zouhair Guennoun was born in Fès, Morocco in 1964. He received his engineering degree in Electronics and Telecommunications from the Electronics and Electrical Montefiore Institute, ULG Liege, Belgium in 1987; his M.Sc. degree in Communication Systems from the EMI School of Engineering, Rabat, Morocco in 1993; and his PhD degree from the same school in 1996. He visited the Centre for Communication Research (CCR) in Bristol University, UK, during the period of 1990-1994 to prepare a split PhD. His fields of interest are digital signal processing, error control coding, speech and image processing, telecommunication systems, networks architecture and networks security. Prof. Guennoun is an IEEE senior member (member since 1990); and ex-member of the Moroccan IEEE section executive committee. During 1988-1996 he worked as an Assistant Lecturer in the EMI School of engineering, and from 1996 he is working in the same school as a Professor Lecturer. Currently, he is in charge of the research team of Smart Communications-ERSC (formerly known as LEC) as part of the research center in engineering sustainable and smart systems at EMI, University Mohammed V in Rabat. He can be contacted at email: zouhair@emi.ac.ma.

Adnane Addaim He received his master diploma in 2001 and his Ph.D. degree in 2008, both in satellite communication from Mohammadia School of Engineers (EMI), Morocco. From 2002 to 2003, he was employed at SIEMENS.AG, as Engineer, responsible of the implementation of the supervision network of the Meditelecom GSM Network, in Morocco. From 2004 to 2009, he was teaching assistant at EMI and research engineer at Centre for Space Research and Studies (CRES, EMI) working on research projects dealing with the design of university microsatellite. He is recipient of the first prize of the 2007-2009 best PhD thesis in the field of Sciences and technologies at Mohammed V university. From Mars to August 2010, he was with post-doctoral scholarship at the Satellite Communication and Networking Laboratory (SCNL) at the faculty of engineering, University of Genoa. From 2010 to 2020 was a professor lecture at ENSA Engineering School at Kenitra, Morocco. Currently, he is a professor lecturer at the EMI Engineering School at Rabat, Morocco. His current research interests include signal processing, wireless communication networks and satellite communication systems. He can be contacted at email: addaim@emi.ac.ma.