Mobile Agents with Recurrent Neural Networks-based Computing Model for Echo Cancellation Problem

F. Bonanno
Department of Electrical, Electronics and Informatics Engineering
University of Catania
Catania, Italy

G. Capizzi
Department of Electrical, Electronics and Informatics Engineering
University of Catania
Catania, Italy

G. Lo Sciuto
Department of Engineering
Roma Tre University
Rome, Italy

Abstract—The purpose of this paper is to draw attention to a novel solving method for AEC problem and to search for a solution based on mobile agents (MAs) technology. Several applications benefit already by the use of MAs technology and we now want to join a soft computing technology as recurrent neural networks (RNNs) for this problem's area in communication systems. In this paper we propose a MAs with RNNs-based, so as pipelined recurrent neural networks (PRNNs), computing model for AEC's problem in communication systems. Prediction of echo paths can be performed by RNNs and PRNNs based processing. The results about the faced problem in communication systems, where the use of MAs with RNNs implementation might be an improvement over a more conventional solutions, are here summarized, presented and evaluated. Satisfactory performance in echo cancellation were obtained. The two echo signals input, as echo remote and echo local are provided as inputs to the RNN and PRNN and the echo output prediction shows a relevant reduction evaluated as 60 db.

I. INTRODUCTION

Several are the application of adaptive filtering algorithms in communication systems problems as for speech recognition, echo cancellation, interference suppression, noise cancellation and acoustic echo cancellation. There are also two main categories of audio analysis problems area that could be investigated as sound matching and speech recognition.

Real-time speech recognition is an important task in current digital communication systems such as mobile telephone systems, adaptive filtering, algorithm for echo cancellation etc... In this paper we deal with the use of mobile agents (MAs) technology with adaptive filtering for thefor echo cancellation problem. The agent concept has been widely adopted in many areas such as: control system, network management, information management, E-commerce.

A mobile agent is the composition of computer program and data which can travel from one computing platform to another. The agent technology becomes popular for the reasons such as: parallel performance of tasks, dynamic adaptation to changing conditions, easy deployment of new program and being able to exchange information. In a mobile agent network, agents can carry data and programs while moving from one computing platform to another and one task can be decomposed into several sub-tasks. These agents work cooperately and dynamically adapt themselves to the changing environment and as known scalability is one important feature
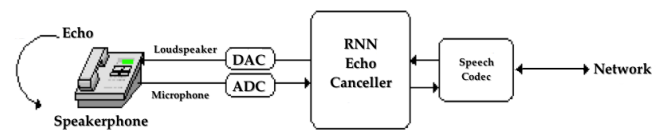

Fig. 1. A problem in Acoustic Echo Cancellation: Line/Network Echo Cancellation.

of an agent network.

Several are the existing available agent platforms including (MOLE, Aglets, Concordia, Ara, TACOMA, and Mobile-C is an embeddable mobile agent system compliant with Foundation for Intelligent Physical Agents (FIPA) that is an internationally recognized agent standards.

We have implemented common RNNs and PRNNs for adaptive filtering but in recent studies appeared in literature, to reduce the computational complexity of the bilinear recurrent neural network (BLRNN), a novel low-complexity nonlinear adaptive filter with a pipelined bilinear recurrent neural network (PBLRNN) was presented by some researchers.

The present paper in this area includes development and implementation of new computing model for adaptive filtering by using MAs in conjunction with RNNs. MAs is one promising new paradigms for distributed application. A mobile agent consists of the program code and the program execution state. Initially, a mobile agent resides on a computer called home machine or dispatching server. The agent is then dispatched to execute on a remote computer called mobile agent host. When a mobile agent is dispatched, its entire code and the execution state are transferred to the mobile agent host. The host provides a suitable execution environment for the mobile agent.

A. The Acoustic Echo Cancellation Problem

Echo Cancellation is used to enhance speech for Radio, Mobile, VoIP applications are available for echo cancellation solutions including acoustic echo cancellers (AEC) and line or network echo cancellers. AEC is an essential part for providing voice quality enhancement in telephone communications (see Fig. 1).
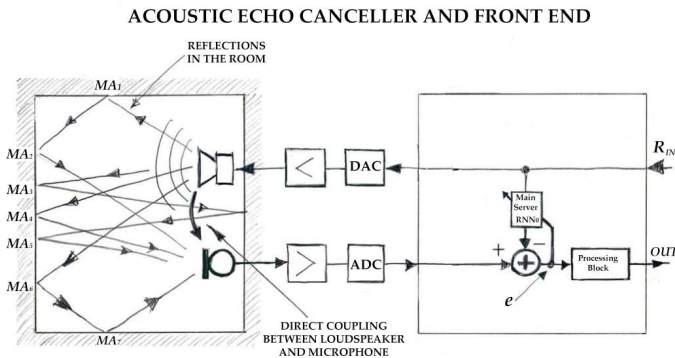
ACOUSTIC ECHO CANCELLER AND FRONT END

Fig. 2. Schematic of a proposed echo cancellation system based on MAs with RNNs and a main Server RNN0

Cancellation is the reduction of the reflected copies of a direct path wave in a signal. An AEC operates on the digitally sampled audio signals of the communication device. The transfer function of the acoustic environment from the loudspeaker to the microphone on the device is estimated to cancel the received echoes from the microphone signal then an AEC is required.

An adaptive filter is conventionally used in voice echo cancellation to accommodate the time varying nature of the echo path. The filter learns the path when the far-end speaker is talking and the near-end speaker is silent and adjusts its coefficients according to the algorithm optimization. For an adaptive filter to learn the echo path it must have an undisturbed reference signal to adapt to. Unfortunately in double-talk detection this filtering scenario cannot be admitted as the near-end speaker may want to interrupt the far-end speaker. In other words, the near-end and far-end speakers talking simultaneously or double-talk resulting modified reference signal.

Non-linear processing is the removal of residual echo left by the adaptive filter. Residual echoes are the un-modeled components of the echo path. Most used adaptive filters are linear and can only cancel the linear portions of the echo path. Thus the nonlinear portions cannot be removed via the adaptive filter and a residual echo removal follows the filter to handle nonlinear portions of the echo remaining. We have gained a large experience in the development and implementation of echo cancellation solutions and now we use MAs with RNNS as shown in Fig. 2.

B. Non-conventional Applications of Acoustic Echo Cancellation

The thinking of people about AEC is its application as a requirement of a conferencing speakerphones or using a wireless handset in hands-free mode. In these situations, the loudspeaker and microphone are enclosed in the same device. Therefore, the physical characteristics of the device help shape the echo path. AEC can be applied to any voice communication system requiring to achieve a high quality full-duplex conversation. For example, AEC can be applied to a drive-thru order post, home intercom systems, baby monitors, patient-care intercom systems in hospitals and imaging centers, VoIP communications on laptops, videophones, and human/machine interfaces. All of these applications present their unique set of challenges.

In drive-thru order posts, reflections off of curbs and other various buildings and structures create an unique acoustic environment to every deployment. The impulse response (echo path) will be very dissimilar to that of a typical office environment and potentially could have a long echo tail. Besides the uniqueness of the echo path, a drive-thru application also has to be able to handle the non-stationary aspects of the background noise. This makes a noise reduction algorithm a requirement with AEC. There are also applications in which the loudspeaker and microphone are not physically tied to the same device, as in distributed multimedia systems. This reduces the acoustic coupling between loudspeaker and microphone. In this situation assuring synchronization between the sampling rates of the loudspeaker and microphone becomes an additional burden.

At present, most teleconferencing systems involve a single full-duplex audio channel for voice communication. These systems usually employ an acoustic echo canceler to remove undesired echoes that result from coupling between the loudspeaker and microphone. As these systems evolve to transparent audio-video medium, the need for enhanced sound realism becomes more important.

This need leads to consideration of multichannel audio, which at a minimum involves two channels, i.e., stereophonic sound. However, before full-duplex stereophonic teleconferencing can be deployed, the AEC problem must be solved.

In this section we have reported these considerations in order to discuss preliminary some unsuccessful attempts in AEC problems area. Several applications benefit already by the use of mobile agents technology and we now want to use a soft computing technology as RNNs for this problem area in communication systems. In this paper we propose a MAs with RNNs and PRNN-based computing model for AECs problem in communication systems. Prediction of echo paths can be performed by MAs-RNNs based processing. The results about the faced problem in communication systems, where the use of MAs implementation coupled with RNNs might be an improvement over a more conventional solutions, are here summarized, presented and evaluated. As mentioned we do not know any satisfactory solution to the echo cancellation problems so basically in this paper a computing model and algorithm is presented for RNNs based adaptive filtering with application to AEC. This computing model can be called as generalized MAs with RNNs-PRNN and is derived as a MAs implementation. The basics of the implementation are then introduced so as the obtained results.

II. SOME TECHNIQUES FOR AEC

In applications such as acoustic echo cancellation the impulse response of the system often reaches over 100ms in length. This would require an adaptive FIR filter with over 1000 coefficients. The linear convolution and the update of the adaptive filter with this length creates a significant computational burden for applications that require low power processors. The application of the adaptive IIR filters often fail to produce the desired results despite their reduced complexity is because the adaptation of the IIR filter contains many local minima and instabilities. As the efficiency of Fast Fourier Transforms (FFTs) have improved, block processing and frequency domain adaptive filters (FDAF) were realized on low power DSPs.

FDAF provide several advantages over its time domain counterpart. Besides being able to perform the filter convolution by a multiplication in frequency domain, also the length of the adaptive filter are effectively decimated by the transformation. Thus, the computational complexity of the adaptive algorithm is reduced. In addition FDAF can also provide an increased convergence speed.

AEC must incorporate a sub-band adaptive filter whose adaptation speed should be superior against conventional solutions As mentioned earlier, applications such as acoustic echo cancellation can have long echo paths, resulting in a large delay and memory requirement. This disadvantage can be overcome by methods such as the multidelay adaptive filters. In this approach the block size can be smaller than the required time domain adaptive filter. In this paper an MAs based algorithm is presented for adaptive filtering in the frequency-domain.

A. Adaptive Filtering in Echo Cancellation

The Echo Cancellation based on Adaptive IIR Filtering is here summarized. Echo cancellation solutions are most often based on a linear FIR adaptive filtering approach. IIR adaptive filters typically use a much smaller number of coefficients to model a system but require additional complexity to control stability during adaptation. This conceptual simplicity has a cost: even a modest approximate model of the echo path has a large number of filter coefficients. A very good approximation of the same real echo path would have much smaller number of coefficients then we use RNNs and then PRNN for adaptive filtering. In literature is reported an outline of the IIR filter-based echo canceller solutions.

In the past the Kalman Filter and the Adaptive Kalman Filter for AEC was also widely used. The Kalman Filter was originally created in 1960 by Rudolf E. Kalman as a re-examination of the filtering and prediction problem using the Bode-Shannon formalism and state-space representation of dynamic systems. This means that the random signals to be worked with are represented as the output of linear systems excited by white noise, and such linear systems are themselves described by first order difference equations.

III. MOBILE-AGENT BASED COMPUTING MODEL

The most commonly used computing model is called client/server based, where individual sensors (the clients) send raw data or preprocessed data to a processing center (the server) and data integration is carried out at the center. It's use still resist today for distributed computing too. Some drawbacks are due to this computing model which might prevent it from being used in sensor networks. Firstly, client/server-based computing generally requires many round trips over the network in order to complete one transaction. The network connection needs to be alive and healthy the entire time of the transaction, otherwise the transaction has to restart if it can at all. Secondly, some kind of super-nodes in the sensors network, served as the processing centers, have bigger storage, higher computing capabilities, and more energy. However in some automatic and homogeneous sensor networks this is not always occur being the unreliability and low bandwidth of the wireless link used in sensor networks. The rising demand on processing power and the need to conserve bandwidth on large, slow networks claim for several new approaches appeared but

possibly the most interesting among them is the mobile agents paradigm.

MAs are a special case of mobile code, i.e. processes that can move from one host to another and resume execution at the new host without actually restarting. There is no final definition of what is a MA, but attempts to classify autonomous agents led someone to a general definition. The difference between the client/server-based computing and mobile-agent-based computing models are well described in literature. In this latter model, instead of each sensor node sending raw data or preprocessed data to the processing center, the processing code is moved to the data locations through mobile agents. An agents decide their own course of action, within the bounds of the program in the context of software agents. This is the meaning of the sentence: Agents are autonomous.

In this section, we present the basics of the computing model based on the MAs and the following features that respond to the unique challenges posed by the sensor network.

A. Client/server-based computing versus Mobile-agent-based computing

Notable benefits over conventional distributed programming paradigms are provided by MAs. The mobile agent is a special kind of "software". Once it is dispatched, migrate from node to node performing data processing autonomously. The structure of a mobile agent has four attributes: identification, itinerary, data, and processing code. Identification uniquely identifies each mobile agent. Data is the agents data buffer, which carries a partially integrated result. Itinerary is the route of migration. It can be fixed or dynamically determined based on the current network status and the information gain. A processing code carries out the integration whenever the mobile agent arrives at a local sensor node.

While in a client/server-based model, data is the migration unit is in the MAs based model, the migration unit is "mobile agent". Therefore, the agent release results and terminate its itinerary any time the integration accuracy satisfies the requirement and this feature also saves both network bandwidth and computation time since unnecessary node visits and agent migrations are avoided. However, for client/server-based computing, there will be increased queuing delay as the number of clients increases so that result in longer processing delay and more potential drops at the server side. In sensor networks the number of nodes could be also hundreds or even thousands.

The main properties of MAs are:

1) Scalability: The performance of the network is not affected when the number of sensor nodes is increased. Agent architectures that support adaptive network load balancing could do much of a redesign automatically.

2) Reliability: Mobile agents can be sent when the network connection is alive and return results when the connection is restablished. Therefore, the performance of the mobile-agent-based computing model is not affected much by the reliability of the network.
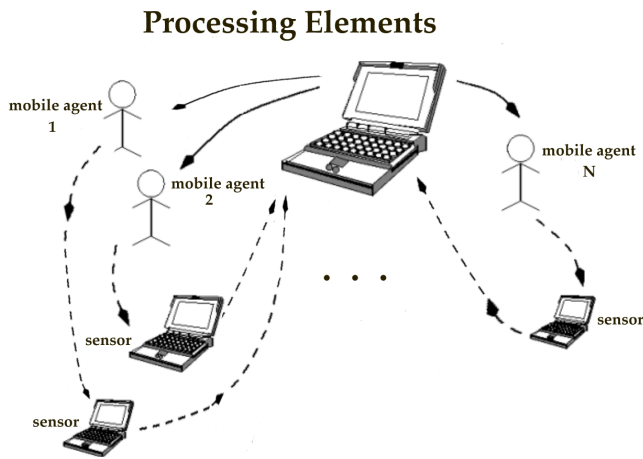
Processing Elements

Fig. 3.   General Schematic of MAs-RNNs based computing model for N sensors node.

Fig. 4.   The selected RNN as a MA.

Fig. 5.   The selected PRNN as a MA for improved performance in AEC.

3) Extensibility and task adaptivity: Mobile agents can be programmed to carry different task-specific integration processes which extends the functionality of the network.

4) Energy awareness: The itinerary of the mobile agent is dynamically determined based on both the information gain and energy constraints. It is tightly integrated into the application and is energy efficient.

5) Progressive accuracy: A mobile agent always carries a partially integrated result generated by nodes it already visited. As the mobile agent migrates from node to node, the accuracy of the integrated result is always improved assuming the agent follows the path determined based on the information gain.

The increasing in popularity of MAs led to the development of several programming languages specifically designed. Telescript was perhaps the first and most well known language. Java is currently the number one choice of mobile agents developers. It is Javas characteristics that favour for developing MAs; it is inherently platform independent and a de facto standard in platform independent computing.

IV. THE DEVELOPMENT OF THE PROPOSED MAs-RNNs AND PRNNs BASED APPROACH FOR AEC

This section documents the implementation and the simulation results with the devised MAs-RNNs and PRNNs based computing models and MAs were independent objects capable to achieve the AEC tasks. Based on users requests, the MAs start their journey and move autonomously among hosts. Figure 3 show the general schematic for N sensors in this scenario but overall behavior for AECwas considered in the paper.

A. Description

The prediction is performed at the listeners in a distribute manner using MAs-RNNs or PRNNS. The concept of the entire computing model is a distributed system, then the information is sent to the server using MAs based computing
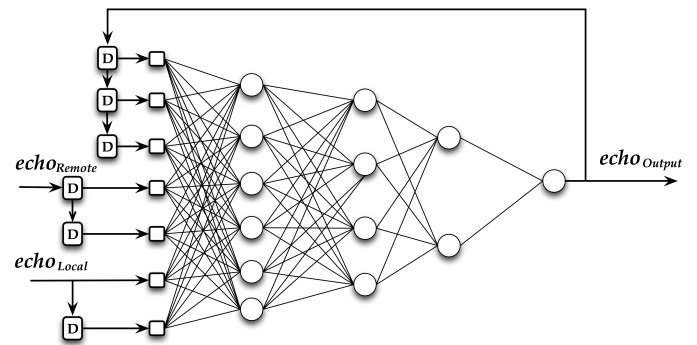
methods.

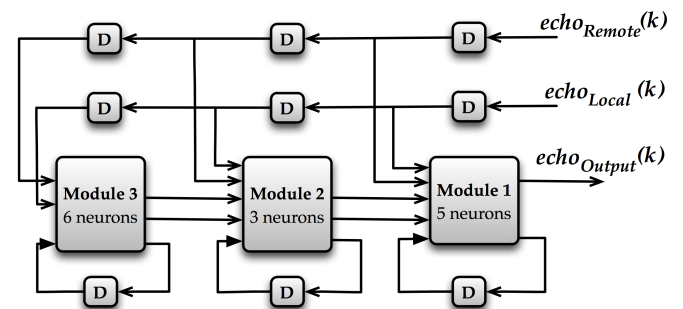However during the implementation of this computing model a few problems became apparent mainly due to the platforms to be adopted, but the use of an MAs-RNNs approach avoids the coarse approximation sometimes joined to imprecise information on the voice, echoes signals.

To our problem now, i.e. as to implement RNNs in the MAs computer hybrid model. Initially for RNNs implementation we used RNS (Recurrent Network Simulator) which is a simulator for recurrent neural networks.

RNSs features include:freely choosable connections, no restrictions besides memory or CPU constraints delayed links for recurrent networks, fixed values or thresholds can be specified for weights(recurrent) back-propagation, Hebb, differential Hebb, simulated annealing and more, patterns can be specified with bits, floats, characters, numbers, and random bit patterns with Hamming distances can be chosen for your user definable error functions, output results can be used without modification as input. However we mention as is wanted the use of RNNs as a guide to the agents, and then Repast (Recursive Porous Agent Simulation Toolkit) is a free and open source agent modeling toolkit under continual development by Argonne. It can be thought of as a specification for agent-based modeling services or functions. It provides an integrated set of libraries for neural networks so as genetic algorithms and other topics. Finally we favour the use of C++ for all implementedMAs in the current our application that will be shown automatically on the display. The system is started by creating a new agent of the Mobile Server and once created, the server shows the network set-up window.
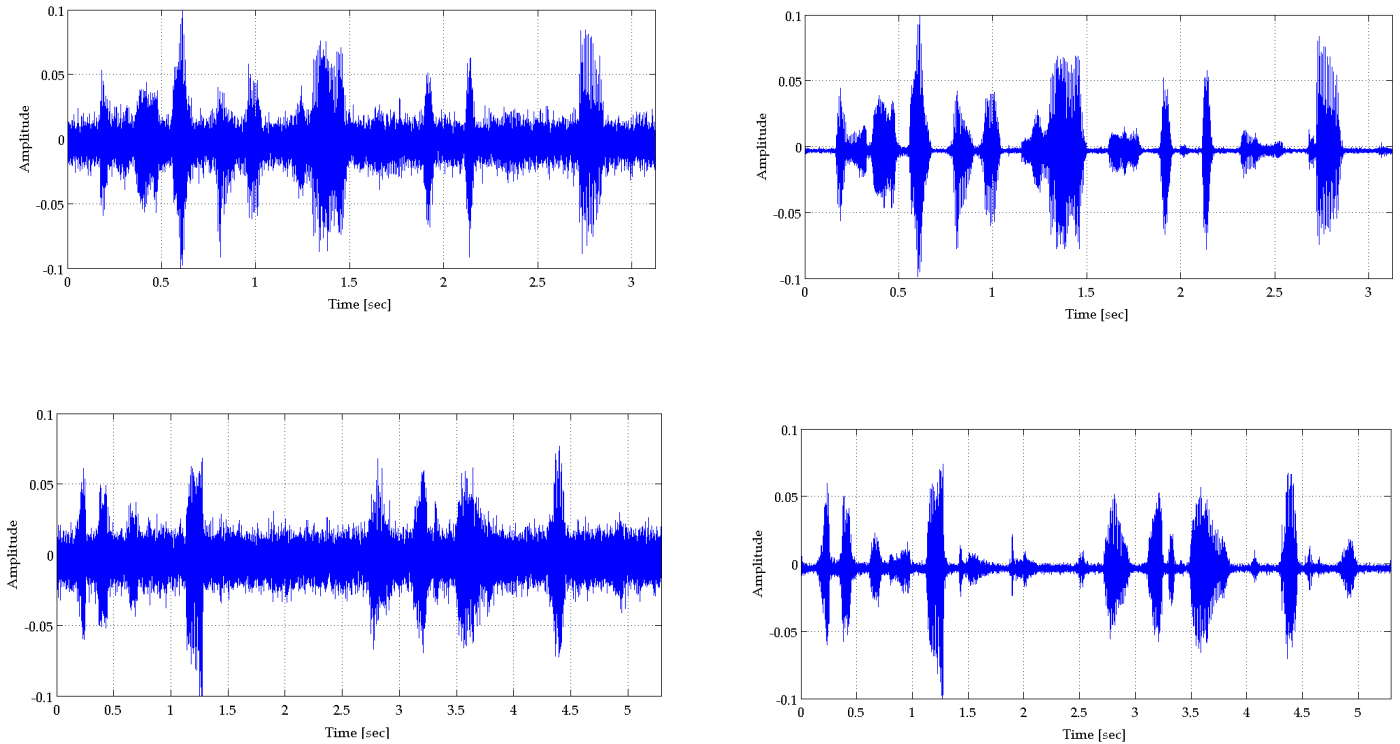
Fig. 6.   Noisy signal on left and the signal after echo reduction on the right.

V.   RESULTS

The authors have initially gained experiences by the use of MAs-RNNs and these were designed as shown in Fig. 4, but however in the present work better MAs-PRNNs based implementation and results are reported being several the advantages raised by their accurate implementation. An hybrid kind of neural network is the so called PRNN introduced by Haykin and Li in 1995. It consists of a modular nested structure of small scale fully connected RNN and a cascaded of FIR adaptive filter.

In the PRNN configuration the single module connection is well described and depicted in literature, joined with relative mathematical equations. PRNN is a modular network made of a number of RNNs as its modules with each module consisting of some neurons and the selected network for the present echo cancellation application consists of three modular layers, with relative neuroprocessing units, as shown in Fig. 5. For both MAs with RNNs, or PRNNs, the number of layers, modular layers and neurons were defined by extensive simulation tests in the corresponding implemented recurrent neural models.

The implemented MAs with RNNs, or PRNNs, have been trained, tested using several speech voice, echoes data samples collected from public speeches of different people and voices. This latter kind of network shows a better prediction capability of non linear behavior data and to model complex phenomena coming from several different physical contributes due to the modular structure which provides analysis and understanding of the basic contribution to reconstruct the overall behavior.

The signals processing is relative to signals registered at the University of Catania coming from the microphone array. For testing the MAs-PRNNs based computing algorithms a database of signals was available with a sampling rate of 8 kHz. They are divided in frames of ten thousand samples

(corresponding to an analysis frame-interval of 3-5.3 ms).

In Fig. 2 is shown as the signal is corrupted by many types of noise, as the reflection in the room, or occurring in an environment, as shown in Fig. 2. For this reason the proposed approach should be highly reliable in presence of these noisy signals. The experiments show as the average echo reduction echo removing is about in the range 40 dB and 30 dB in a widely considered signals relative for the main speaker and at several SNR ratios, for a considered signal voices database registered at the University of Catania. By addressing the AEC problem by this approach, the time is not considered as a second dimension of the input space, but it is implicitly coded in the structure of a recurrent network topology or modular RNN.

The MAs-PRNNs based echoes output prediction is so obtained, but here the result is reported in Fig. 6 only for a node sensor. Satisfactory performance of echo cancellation were obtained also for the other nodes. The two echo signals input, as echo remote and echo local, so as the echo output prediction are shown in Fig. 6. This echo output prediction for the selected node is relative to the best result provided by MAs-PRNNs implementation.

A selective management of the temporal memory is also possible thanks to their computational flexibility. The individual weights of the three modules in Fig. 5 are adjusted in independent manner. Moreover PRNNs show a stronger time memory with respect to a standard RNNs with back propagation through time training algorithm. A large amount of data were processed in order to find a RNN and PRNN structure able to reproduce the behavior of a MAs soft-computing based echo cancellation solutions. The MAs based echoes output prediction in order to evaluate the echo-cancellation is so obtained. The result were calculated for the overall system

keeping in account the main speaker.

Satisfactory performance in echo cancellation were obtained. The two echo signals input, as echo remote and echo local are provided as inputs to the RNN and PRNN and the echo output prediction shows a relevant reduction evaluated as 60 db. This echo output prediction is relative to the best result coming from MAs-PRNNs implementation.

VI. CONCLUSIONS

Several applications benefit already by the use of mobile agents technology and we now want to use a soft computing technology as RNNs and PRNNs for this problem area in communication systems. In this paper we propose a MAs with RNNs-PRNNs-based computing model for AECs problem in communication systems.

Prediction of echo paths can be performed by RNNs based processing. The results about the faced problem in communication systems, where the use of MAs implementation with RNNs might be an improvement over a more conventional solutions, are here summarized, presented and evaluated.

As mentioned we do not know any satisfactory solution to the echo cancellation problems so basically in this paper a computing model and algorithm is presented for RNNs based adaptive filtering with application to AEC. The basics of the implementation are introduced so as the obtained results.

The experiences with the results, gained on the echo cancellation problems, by the implemented MAs-PRNNs show better performance versus MAs- RNNs computing model. However the performance of this approach can not be compared versus more conventional MAs applications or distributed computing system in AEC problems being a novel implementation in this field but the determination if rising any advantage of using other platform for the MAs with RNNS or PRNNs has to be investigated.

REFERENCES

[1] M. Sondhi, D.R. Morgan, J.L. Hall, "Stereophonic acoustic echo cancellation-an overview of the fundamental problem," *IEEE Signal Processing Letters,* Vol. 2, no. 8, pp. 148-151 (1995).

[2] Haiquan Zhao, Xiangping Zeng, Zhengyou He, "Low-Complexity Non-linear Adaptive Filter Based on a Pipelined Bilinear Recurrent Neural Network," *IEEE Transactions on Neural Networks,* vol.22, no. 9, pp.1494-1507, Sept. 2011.

[3] S. Haykin, "Adaptive Filter Theory," Englewood Cliffs, Prentice-Hall, New York (2001).

[4] R.H. Glitho, E. Olougouna, Pierre, Samuel, "Mobile agents and their use for information retrieval: a brief overview and an elaborate case study," *IEEE Network,* vol.16, no.1, pp.34-41, Jan/Feb 2002.

[5] L. Ismail and D. Hagimont "A Performance Evaluation of the Mobile Agent Paradigm" *ACM SIGPLAN NOTICES,* pp. 306–313, ACM Press (1999).

[6] S. Haykin, "Neural Networks and Learning Machines," Englewood Cliffs, Prentice-Hall, New York (2008).

[7] F. Bonanno, G. Capizzi, C. Napoli, "Some remarks on the application of RNN and PRNN for the charge-discharge simulation of advanced Lithium-ions battery energy storage" *2012 IEEE International Symposium on Power Electronics, Electrical Drives, Automation and Motion (SPEEDAM)* pp. 941-945, 20-22 June 2012.

[8] G. Capizzi, F. Bonanno, C. Napoli, "Recurrent neural network-based control strategy for battery energy storage in generation systems with intermittent renewable energy sources," *2011 IEEE International Conference on Clean Electrical Power (ICCEP)* pp. 336-340, 14-16 June 2011.

[9] G. Capizzi, F. Bonanno, C. Napoli, "Hybrid neural networks architectures for SOC and voltage prediction of new generation batteries storage," *2011 IEEE International Conference on Clean Electrical Power (ICCEP)* pp. 341-344, 14-16 June 2011.

[10] F. Bonanno, G. Capizzi, S. Coco, C. Napoli, A. Laudani, and G. L. Sciuto, "Optimal thicknesses determination in a multilayer structure to improve the SPP efficiency for photovoltaic devices by an hybrid FEM Cascade Neural Network based approach," *2014 IEEE International Symposium on Power Electronics, Electrical Drives, Automation and Motion (SPEEDAM)* pp. 355-362, 18-20 June 2014.

[11] F. Bonanno, G. Capizzi, G. L. Sciuto, C. Napoli, G. Pappalardo, E. Tramontana, "A novel cloud-distributed toolbox for optimal energy dispatch management from renewables in IGSs by using WRNN predictors and GPU parallel solutions," *2014 IEEE International Symposium on Power Electronics, Electrical Drives, Automation and Motion (SPEEDAM)* pp. 1077-1084, 18-20 June 2014.

[12] C. Napoli, F. Bonanno, G. Capizzi, "An Hybrid Neuro-Wavelet Approach for Long-Term Prediction of Solar Wind", *IAU Symposium No. 274, Advances in Plasma Astrophysics,* pp. 247-249, Giardini Naxos, Italy (2010).

[13] C. Napoli, F. Bonanno, G. Capizzi, "Exploiting Solar Wind Time Series Correlation with Magnetospheric Response by Using an Hybrid Neuro-Wavelet Approach", *IAU Symposium No. 274, Advances in Plasma Astrophysics,* pp. 250-252, Giardini Naxos, Italy (2010).

[14] G. Capizzi, F. Bonanno, and C. Napoli, "Hybrid neural networks architectures for soc and voltage prediction of new generation batteries storage, in Proc. *IEEE, International Conference on Clean Electrical Power (ICCEP),* pp. 341344, 2011.

[15] G. Borowik, M. Woźniak, A. Fornaia, R. Giunta, C. Napoli, G. Pappalardo, E. Tramontana, "A software architecture assisting workflow executions on cloud resources", *International Journal of Electronics and Telecommunications,* vol. 61, no.1, pp. 17-23, 2015.

[16] G. Capizzi, F. Bonanno, C. Napoli, "A new approach for lead-acid batteries modeling by local cosine" in Proc. *IEEE Symposium on International Power Electronics Electrical Drives Automation and Motion (SPEEDAM),* pp.1074-1079, 2010.

[17] F. Bonanno, G. Capizzi, A. Gagliano, C. Napoli, "Optimal management of various renewable energy sources by a new forecasting method", in Proc. *International Symposium on Power Electronics, Electrical Drives, Automation and Motion (SPEEDAM),* pp. 934-940, 2012.

[18] F. Bonanno, G. Capizzi, G. Lo Sciuto, C. Napoli, G. Pappalardo, E. Tramontana, "A cascade neural network architecture investigating surface plasmon polaritons propagation for thin metals in openmp," *Springer International Publishing,* pp. 22-33, 2014.

[19] C. Napoli, G. Pappalardo, E. Tramontana, Z. Marszałek, D.Połap, M. Woźniak, "Simplified firefly algorithm for 2D image key-points search", in Proc. *IEEE Symposium on Computational Intelligence for Human-like Intelligence,* pp.118-125, 2014.