Abstract—This article introduces Random Error Sampling-based Neuroevolution (RESN), a novel automatic method to optimize recurrent neural network architectures. RESN combines an evolutionary algorithm with a training-free evaluation approach. The results show that RESN achieves state-of-the-art error performance while reducing by half the computational time.

Index Terms—neuroevolution, evolutionary algorithms, meta-heuristics, recurrent neural networks

I. INTRODUCTION

A recurrent neural network (RNN) is a class of artificial neural network that has feedback connections between nodes. Thanks to this recurrence, RNNs are particularly good for tackling time-dependent (or sequential) problems. But, due to this same feature (i.e., the recurrence), they are hard to train [1]: small changes on its components may produce a big performance deviation [1].

Several alternatives have been proposed to deal with the sensitivity of RNN design, including specific node architectures (e.g., GRU [2] and LSTM [3]), for their fully automatic design [4]. However, in spite of great improvements made so far [5], finding the best design is still an open issue. Particularly, optimizing an RNN is (time and computation wise) a very demanding task. Therefore, a low-cost approach is desirable.

This article summarizes our previous work [6], in which we proposed a fast and accurate method to optimize the architecture and the weights of an RNN.

II. RANDOM ERROR SAMPLING-BASED NEUROEVOLUTION

Given an input $X$, an output $Y$, a search space of RNN architectures (ARQ) and look back (or time steps, LB), we considered the problem of maximizing the fitness($X, Y$)$=p_t$, the probability of finding a set of weights whose performance is below the defined threshold (i.e., MRS [7]).

To solve the stated problem, we proposed RESN, a $(\mu + \lambda)$ EA. At a glance, the population is a set of solutions, where each solution represents an RNN architecture. The initial population is randomly set by the Initialize function. Later, the population is assessed by the Evaluate function, that computes $p_t$ for each solution. Then, the population is evolved by the selection, mutation, evaluation, replacement, and self-adjustment operations. Once the termination criterion is met, i.e., the number of evaluations is greater than the budget (max_evaluations), the Best solution (i.e., the one with the highest $p_t$) is selected and trained using Adam [8] for a predefined number of epochs.

Fig. 1 summarizes RESN. The proposed approach combines evolutionary computation and machine learning techniques to optimize the architecture and the weights of an RNN.

III. EXPERIMENTAL STUDY

We tested RESN on four problems: the sine wave, the waste generation prediction problem [9], the coal-fired power plant flame intensity prediction problem [10], and the EUNITE load forecast problem [11]. Also, we proposed four experiments: E1: RESN vs. Gradient-based Architecture Optimization, we compared RESN against (i) a modified version of the same algorithm (i.e., a version that replaced the MRS by the results
of Adam training), (ii) the Short training algorithm, and (iii) a Random Search algorithm. E2: RESN vs. Neuroevolution, we benchmarked RESN against EXALT [13]. E3: Optimization Time, we logged the execution times. And E4: RESN vs. Expert Design, we compared our results against the winner of the EUNITE load forecast competition and to recent solutions to the same challenge [14].

Summarizing E1, (E1.i) the results of RESN exceed GDET (i.e., a modified version of RESN that uses training results to evaluate the performance of a solution). On average, RESN obtained a MAE of 0.105 while GDET got a 0.142 (Wilcoxon rank-sum test p-value equals to 0.001: significant). Then, (E1.ii) RESN was compared to Short Training [12]. The results show that there is no significant improvement in the error (i.e., Wilcoxon rank-sum test p-value equal to 0.665), however, RESN cut by half the optimization time (i.e., test E3). Table I presents the results, where MAE stands for the MAE of the final solution, and Time for the total time (i.e., optimization and training of the final solution) in minutes.

| TABLE I                      |                      |                  |
|------------------------------|----------------------|-----------------|
|                              | Short Training       | RESN            |
|                              | MAE (Time [min])     | MAE (Time [min])|
| Mean                         | 0.073 97             | 0.079 51        |
| Median                       | 0.073 70             | 0.073 45        |
| Max                          | 0.076 405            | 0.138 103       |
| Min                          | 0.071 33             | 0.069 40        |
| SD                           | 0.001 75             | 0.017 13        |

To conclude E1, we compared RESN against random search (E1.iii). Despite the relatively good error performance of random search, with an average of 0.091, the Wilcoxon rank-sum test revealed that RESN (and Short training) beats random search (p-values are 0.017 and 0.002 respectively). Moreover, random search took nearly 50x the time of RESN (!). Thus, RESN is a fast and accurate approach (test E3).

Later, (E2) we compared RESN against neuroevolution. Summarizing, RESN improved EXALT by ten times (Wilcoxon rank-sum test p-value is 2.958e-06). Table I depicts the mean square error (MSE) of the solution obtained by RESN and EXALT [13] in the coal-fire power plant problem.

| TABLE II                      |                      |                  |
|------------------------------|----------------------|-----------------|
|                              | EXALT                | RESN            |
| 0                            | 0.028749             | 0.005141        |
| 1                            | 0.031769             | 0.006536        |
| 2                            | 0.023095             | 0.003821        |
| 3                            | 0.019229             | 0.005709        |
| 4                            | 0.023170             | 0.003336        |
| 5                            | 0.030691             | 0.006617        |
| 6                            | 0.012879             | 0.017061        |
| 7                            | 0.019358             | 0.004032        |
| 8                            | 0.018151             | 0.001912        |
| 9                            | 0.019475             | 0.013996        |
| 10                           | 0.030016             | 0.006120        |
| 11                           | 0.031207             | 0.002942        |
| Average                      | 0.029412             | 0.006208        |

Finally (test E4), we compared RESN against human expert designed solutions in the EUNITE load forecast problem. Table III presents the results. The column SVM corresponds to [11], the winner of the “Electricity Load Forecast using Intelligent Adaptive Technologies” competition organized by EUNITE, and the other columns, i.e., BP, RBF, SVR, NNWR, KNNRW, and WKNNRW, correspond to the results presented in [13]. NA stands for Not Available. From the results, we concluded that the performance of RESN is comparable to a human expert, i.e., “the error of the best solution found is as good as the best solution proposed by the experts”.

| TABLE III                     |                      |                  |
|-------------------------------|----------------------|-----------------|
|                              | SVM BP RBF SVR NNWR KNNRW WKNNRW RESN |
|--------------------------------|----------------------|-----------------|
| Mean                          | 2.88 NA NA NA NA NA NA 2.28 |
| Median                        | 2.95 NA NA NA NA NA NA 2.24 |
| Max                           | 3.48 NA NA NA NA NA NA 2.37 |
| Min                           | 1.95 1.45 1.45 1.44 1.35 1.32 1.37 |
| SD                            | 0.01 NA NA NA NA NA NA 0.41 |

IV. Conclusions and Future Work
As a summary of this study, we conclude that RESN (which is a training-free algorithm) is a competitive approach to RNN design. Particularly, it achieves a comparable error performance of training-based RNN techniques and neuroevolutionary approaches but considerably reduces the computational time, and it is as good as human expert designed solutions.

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