Ozone forecasting across Belgium with co-evolutionary Neural Architecture Search

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Abstract. Air pollution was the 4th leading risk factor for early death in 2019. Models capable of forecasting nonlinear atmospheric phenomena are difficult to train and optimize consistently. Island Transpeciation [21] is a co-evolutionary neural architecture search technique that can train and optimize architectures and hyperparameters of day-ahead forecasting deep neural networks. Using several years of real-world historical air-quality and meteorological data, we managed to outperform random model search and previous machine learning techniques in accurately predicting ozone across Belgium.

Keywords: forecasting · neural architecture search · deep learning · meta-learning

1 Motivation

Around 400,000 premature deaths per year are caused by air pollution in Europe [3] [9] [10]. Accurate forecasting allows governments to promptly warn the public with low air-quality alerts [7]. Our objective is the search for accurate, country-wide models, for next-day ground-level ozone (O_3) [1] forecasting. This extended encore abstract describes the prior work on Island Transpeciation [21].

2 Main contributions

We developed *island transpeciation* [20] [21] (Fig. 1), to optimize Deep Neural Networks (DNN) [18] [11] [4] in forecasting. Co-evolution between different optimizers [14] [22] is achieved via the transpeciation evolutionary operator, under a Neural Architecture Search (NAS) [6] [25] [24] setting. **Contributions:**

- A new Evolutionary Algorithms (EA) [23] operator: *transpeciation*.
- Island transpeciation: an automated parallel [17] [5] and distributed [12] [2] NAS, featuring hardware hot-plugging and fault-tolerance.

– Multiple-Input Multiple-Output (MIMO), Nonlinear Auto Regressive eXogenous (NARX) DNN: A single model prototype for country-scale air quality forecasting.
– Ozone forecasting deep learning model configuration suggestions.

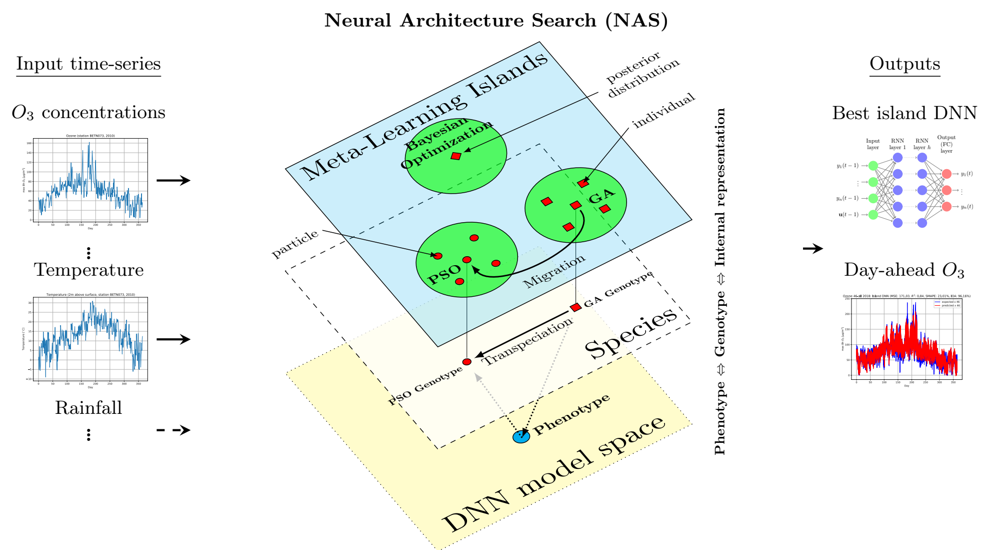

Fig. 1. Day-ahead ozone forecasting top-level view, using the island transpeciation NAS [21]. The transpeciation operator (middle layer: species) allows the cooperation and competition between incompatible optimizers via: transformation and migration of candidate model solutions. In this illustration: Bayesian Optimization (BO) [15] island cooperates with a Genetic Algorithm (GA) [16] [8] and Particle Swarm Optimization (PSO) [19].

3 Results and Conclusion

MIMO NARX DNN (Fig. 1) can successfully predict country-wide, next-day O_3 pollution episodes, on real-world time-series (46 Belgian monitoring stations [1] data, from 1990 to 2018). The main negative is extended model training times. This co-evolutionary meta-learning [13] approach balances model training times versus model size trade-offs, via the asynchronous cooperation and competition of the underlying optimizers. Finally, there should be a balanced consideration between the number of islands and the total amount of NAS iterations.

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