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A multi-objective neural network trained with differential evolution for dynamic economic emission dispatch

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ABSTRACT

Multi-objective optimisation has received considerable attention in recent years as many real world problems have multiple conflicting objectives. There is an additional layer of complexity when considering multi-objective problems in dynamic environments due to the changing nature of the problem. A novel Multi-Objective Neural Network trained with Differential Evolution (MONNDE) is presented in this research. MONNDE utilizes Neural Network function approximators to address dynamic multi-objective optimisation problems. Differential Evolution (DE) is a state of the art single objective global optimisation problems and will be used to evolve neural networks capable of generating Pareto fronts. The proposed MONNDE algorithm has the added advantage of developing an approximation of the problem that can produce further Pareto fronts as the environment changes with no further optimisation needed. The MONNDE framework is applied to the Dynamic Economic Emission Dispatch (DEED) problem and performs equally optimal when compared to other state of the art algorithms in terms of the 24 h cost and emissions. This research also compares the performance of fully and partially connected networks and discovers that dynamically optimising the topology of the neural networks performs better in an online learning environment than simply optimising the network weights.

1. Introduction

The Dynamic Economic Emission Dispatch (DEED) problem [1] is a dynamic multi-objective optimisation problem. The aim of this problem is to optimise a set of power generators over a period of time in a manner that both minimizes: (1) The *power generation operating cost* and (2) The *emission of harmful atmospheric pollutants*. The task of power generation is critical for modern society to function. It is crucial that electricity is generated in a cost-effective and environmentally responsible fashion. Power generator scheduling is a highly complex task due to the many factors that influence the power generation process. There are a number of constraints including: (1) The generator operation limits. (2) The generator ramp limits. (3) Balancing the power demand and network losses. Generators also have varying levels of efficiency in terms of cost and emissions produced, thus making the problem multi-objective. Variation in the power demand over time makes the problem dynamic, i.e. the optimal configuration for the power generators at time t is no longer optimal at time $t + 1$. For utility companies to operate effectively, it is imperative that these power generators are scheduled efficiently. Large increases in running costs would be incurred due to sub optimal power generator scheduling. In recent years, many countries have pledged to reduce their carbon footprint [2]. As a result, utility companies must consider the environmental cost of generating electricity in addition to the financial cost. The emission of harmful atmospheric pollutants such as sulphur dioxide (SO_2) and nitrogen oxide (NO) must be kept to a minimum when scheduling power generators.

When searching for an optimum solution that optimises multiple objectives, it is soon apparent that there is no single optimum solution that optimises all of the objectives. The field of multi-objective optimisation is instead concerned with finding a range of solutions that optimises each objective to a different degree. This set of solutions is known as the Pareto optimal set, where each solution is considered to be equally optimal. The DEED problem is also dynamic in nature due to the changing power demand from hour to hour. The field of dynamic optimisation is concerned with the optimisation of a dynamic objective function, i.e. one that changes with time. There are three main factors to consider when addressing dynamic optimisation problems: (1) Discrete vs continuous time. (2) Deterministic vs stochastic change. (3) Finite vs infinite time horizon. Neural networks have proven to be an effective control method for these dynamic optimisation problems. Neural networks are function approximators that are inspired by the biological brain and are commonly used in machine learning research [3]. They operate by reading in a signal through an input layer of

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neurons, this signal is then propagated through the network by weighted connections to subsequent hidden layers of neurons. Neural networks can be either fully connected or partially connected. Fully connected networks have the advantage of being easy to implement as there is no need to select a network topology. The disadvantage is that fully connected networks have more weights that need to be optimised than a partially connected network with the same number of neurons. Partially connected networks have the advantage of having fewer weights to train (and therefore less complexity), have improved generalization and have reduced hardware requirements in physical implementations [4]. This research will explore the performance of partially connected networks for the DEED problem.

This research proposes a novel Multi-Objective Neural Networks trained using Differential Evolution (MONNDE). Differential Evolution (DE) is a state of the art global optimisation algorithm [5]. The effectiveness and robustness of DE makes it a suitable choice for training the weights of the neural network. DE is however a single objective optimisation algorithm, although there have been multi-objective variants of DE proposed e.g. Pareto-frontier Differential Evolution (PDE) [6]. Although the aim in multi-objective optimisation is to find multiple solutions that are in the Pareto front, the aim here is to find the single set of network weights that can output a Pareto front depending on the current state of the environment and current objective weight.

The proposed MONNDE algorithm will be applied to the Dynamic Economic Emission Dispatch (DEED) problem [1]. Many algorithms have been applied to the DEED problem in the literature, however the vast majority of these methods are purely optimisation algorithms and therefore do not produce any approximate functions that are capable of producing solutions the optimisation problem. The focus of optimisation algorithms is to find the optimum configuration of the problem variables to maximize/minimize an objective function. The distinction between the proposed MONNDE and previous approaches in the literature is that MONNDE *learns* to produce solutions on demand whereas previous approaches view the DEED problem purely as an optimisation problem. Once the power demand changes, a multi-objective optimisation algorithm would have to be reapplied to optimise the power generators for the new power demand. This is not the case for the proposed MONNDE algorithm. After the initial training period, no further optimisation is needed for any changes to the power demand. MONNDE builds a function approximator that incorporates the problem characteristics which optimisation algorithms do not do. In short, the MONNDE algorithm applies an optimisation algorithm to the neural network which is used to adjust the problem variables for DEED. Multi-objective optimisation algorithms optimise the DEED problem variables directly. Of course there are many examples in the literature of neural networks being used for economic dispatch [7]. The difference between MONNDE and previous studies is that MONNDE evolves networks capable of producing Pareto fronts for multi-objective problems such as DEED. There are no such examples of this in the literature. The research presented in this paper demonstrates that this is in fact a valid approach. The results presented later show that MONNDE performs on a par with state of the art multi-objective algorithms and can produces Pareto fronts for new power demands with no further optimisation after the initial training period.

This research will also investigate how the proposed multi-objective neural network controllers perform in an online learning environment, i.e. when the environment is susceptible to drastic changes. The research presented in this paper is at the intersection of a number of research areas: multi-objective optimisation, dynamic optimisation, evolutionary computing, neural networks and energy generation. The contributions of this paper are as follows:

1. The design of a novel Multi-Objective Neural Network trained with Differential Evolution (MONNDE) algorithm that can produce a Pareto front for dynamic multi-objective problems.
2. A novel fitness function is proposed that incorporates a Pareto penalty function to help the network to successfully produce a Pareto front at each time step.
3. To compare the performance of both fully and partially connected neural networks for producing the Pareto front
4. To investigate dynamically selecting the network topology as the network is being optimised.
5. To apply the proposed MONNDE to the Dynamic Economic Emission Dispatch problem for both offline and online learning, i.e. when the fitness function dramatically changes in the form of a power generator failure.
6. To investigate the scalability of MONNDE to different size problems.
7. To test MONNDE with new power demands after the initial training period.

The rest of this paper is structured as followed: Section 2 provides a more detailed background into the literature on Multi-Objective Optimisation, Neural Networks, Partially Connected Neural Networks and Differential Evolution. Section 3 outlines the Dynamic Economic Emission Dispatch (DEED) problem that is used to evaluate the proposed MONNDE algorithm. Section 4 describes how the MONNDE algorithm is implemented. The experimental methodology is outlined in Section 5. The results of the experiments are presented in Section 6. Finally, Section 7 draws conclusions based on these results and outline potential future research.

2. Background

This section will start by giving a brief overview of the relevant literature on Multi-Objective Optimisation and its applications. This will be then followed by an overview of Neural Networks followed by Partially Connected Neural Networks. The section will finish with a description of both Differential Evolution and neural network topology and weight optimisation.

2.1. Multi-objective optimisation

Multi-objective optimisation is a sub discipline within optimisation research that explores problems with two or more objectives. These problems have an additional element of complexity due to the conflict that arises when optimising multiple objectives. As the objectives are optimised, there comes a point where by improving upon one object will result in the deterioration of another objective. In multi-objective optimisation problems, the goal is to find a range of solutions, where each solution optimises the different objective with a varying level of significance. They are all considered equally optimal as long as they optimise at least one of the objectives better than any other solution. These optimal solutions are referred to as Pareto optimal solutions [8]. A more strict definition of Pareto optimality states that a solution $\vec{x}$ is Pareto optimal if there exists no other acceptable solution $\vec{y}$ which would improve upon the fitness of one objective and not result in the detriment of the fitness of another objective. Mathematically this can be described as solution $\vec{u} = (u_1,\ldots,u_n)$ is said to dominate solution $\vec{v} = (v_1,\ldots,v_n)$ if $\forall\, i \in \{1,\ldots,n\}, u_i \leqslant v_i \wedge \exists\, i \in \{1,\ldots,n\}: u_i < v_i$. The Pareto optimal set can be defined as $\mathscr{P}^* := \{x \in \Omega| \neq g \exists\, x' \in \Omega \vec{f}(x') \preceq \vec{f}(x)$ where Ω represents the feasible set of solutions and $\vec{f}$ is the vector of objective functions. The Pareto Front can be defined as $\mathscr{P}\mathscr{F}^* := \{\vec{u} = \vec{f} = (f_1(x),\ldots,f_k(x)|x \in \mathscr{P}^*\}$. A comprehensive overview of multi-objective optimisation can be found the work of Coello et al. [9].

The multi-objective framework has proven to be very popular in recent years due as it acknowledges that many real world problems have multiple objectives. A subset of these real world problems include: stock portfolio management [10], software construction management [11], supply chain simulation [12] and design [13]. Some of the most prominent multi-objective optimisation algorithms include: Non-dominated Sorting Genetic Algorithm (NSGA-II) [14], Pareto-frontier