Optimisation of the Global Calculator using Machine Learning

MSc in Applied Computational Science and Engineering Project (Imperial College London)
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Abstract This investigation aims to generate different climate change mitigation pathways with the "Global Calculator" - a complex model used to forecast the world's energy, food and land systems to 2050. Performing a constrained optimisation of the model's input parameter space yields alternative pathways to sustainability.
The key challenge of such an optimisation is to explore a broad parameter space (~*9e50* different parameter combinations) very quickly. To address it, different optimisation methods are considered: Monte-Carlo Markov Chains (MCMC), Generative Adversarial Neural Networks (GANs) and Game Artificial Intelligence (AI) algorithms.
The possibility of generalising these optimisation approaches to other calculators (such as the "EU Calculator" or the "UK Calculator") is considered. Lastly, the challenge of updating the calculator with real-time data is suggested as further work.

I. Introduction

THIS section introduces the calculator, the purpose of optimising it, and the methods considered in doing so.

The Global Calculator is a tool used to inform the climate debate at an international level. As stated by The Paris Agreement's temperature goal, the increase in global average temperature must be below 2 °C [14].

Policymakers, business leaders, NGOs and researchers use the Global Calculator to design their own version of the future up to 2050, see the implications for the climate, and take business decisions in the present accordingly [4].

A. The Global Calculator

The Global Calculator is a free, open-source, and interactive model of energy, land and food systems to 2050 (tool.globalcalculator.org). It can be used to assess a wide range of climate change mitigation pathways.

It has 50 input 'levers' which are organised in clusters and around 60 outputs. Each input lever has four levels of ambition (minimal effort, ambitious effort, very ambitious effort and extreme effort).

B. Optimal lever combinations

Trial-and-error confirms the difficulty of achieving the 2 °C warming limit. Currently, users of the calculator create their pathways by selecting lever combinations by hand. This yields suboptimal lever combinations.

This investigation aims to enable the user to generate optimal lever combinations based on their preferences.

The calculator's parameter space consists of ~*9e50* possible lever combinations. The key challenge addressed is the efficient navigation of such a broad parameter space to yield optimal lever combinations.

C. Efficient navigation of the parameter space

Quickly navigating a large parameter space is a common challenge in the field of Data Analysis and Game Artificial Intelligence (AI). This investigation contributes to the state of the art by applying (and possibly modifying) methods from these fields to optimise the levers of the Global Calculator.

II. Objectives

Users of the Global Calculator tend to create suboptimal pathways for two reasons: Creating a pathway involves setting 50 different levers across a total of 15 sectors and users frequently have industry-specific knowledge. As a result, most levers are set using guesswork.

The objective of this investigation is to enable users of the calculator to specify their levers of interest as constraints and to present them with the corresponding optimal pathways that meet the warming target.

For example, let us assume that the Vegan Society is interested in setting the levers of “Diet”, “Food” and “Land use”. Instead of arbitrarily setting the remaining 41 levers, the proposed functionality would enable them to set their levers of interest as a constraint to find optimal pathways.

III. Methodology

A. Software development

This investigation will be carried out using Python3. Best software development practices will be followed, including constant GitHub integration.

B. Technical decisions

1) Interacting with the Global Calculator

To find optimal lever combinations, it is key to first have an efficient way of interacting with the calculator.

The Excel and web versions of the calculator have proved either slow or unreliable. As such, the model shall be approximated using a feed-forward neural network (NN).

2) Generating training data

Data for the feed forward NN is generated by logging random lever combinations and their output via the web GUI – this is the quickest way of generating data.

The amount of training data that yields a high test-set accuracy shall be determined empirically.

3) Finding optimal lever combinations

This problem can be tackled by several algorithms, including MCMC, GANs, and Game AI (Monte-Carlo tree search (MCTS), evolutionary algorithms and reinforcement learning)

Their performance and suitability to this problem shall be empirically tested.

3.1) MCMC

The optimisation constraints can be expressed as probability distributions. MCMC can be used to find the probability distribution of each lever that maximises the probability of the output distribution.

3.2) GANs

This method can be used to create a generator network that generates random lever combinations that meet the optimisation constraints. In doings so, a discriminator network imposing the constraints would be used.

3.3) Game AI

The calculator can be regarded as a tree structure. Moving a lever in a certain direction can be thought of as moving onto the next branch of the tree. MCTS, evolutionary algorithms, and reinforcement learning are methods suited for exploring these trees.

4) Results visualisation

To visualise the results of the optimiser, the implementation of a web tool is considered. Its design shall be inspired in the start-up White Space Energy. This might be achievable by embedding Tableau data visualisations into a website.

IV. Literature Review

A. Calculators and sustainable pathways

Benchmark pathways to sustainability have been published by the authors of the Global Calculator in [1], [2] and [3]. These include "distributed effort", "consumer reluctance", "low action on forests" and "consumer activism".

Since it was published, the calculator has been used to inform policy, business decisions, and research - as explained in [4]. The UN wrote a report that relied on the results of the calculator [8]. Many research publications use the calculator to aid their analyses, as seen in [5], [6], [7] and [9].

Organisations have developed and published their own pathways, including Shell, Mott-MacDonald, the World Nuclear Association and the Vegan Society.

The use of calculators as a tool for informing climate debate started with the UK calculator. This idea has been upscaled and downscaled, leading to projects such as the EU calculator, city calculators or company calculators [15].

There is no literature discussing optimisation methods for these calculators. This investigation aims to address such a gap.

B. Neural networks as function approximators

To model the Global Calculator, the use of a neural network as a function approximator is considered [13]. An upper bound for the number of neurons of the network is provided in [12].

To generate unbiased training data for the network, the data are sampled via Monte-Carlo methods [16]. The optimal volume of training data is determined empirically.

Developing a framework to model different calculators using neural networks would add to the literature.

C. Optimisation methods

The research challenge of finding optimal lever combinations could be tackled by using MCMC. This technique is used in the numerical approximation of multi-dimensional integrals. Its domains of application include Bayesian statistics, computational physics, computational biology and computational linguistics [17].

On the other hand, GANs would prove useful to generate random lever combinations that meet the optimisation constraints. The generator network oversees creating candidates, whereas the discriminator networks evaluate them according to the optimisation constraints [19]. They have been used in many different fields: Fashion, art, advertising, video games and science [18]

Lastly, this research challenge frequently appears in games – where the action space is nearly continuous, thus leading to exorbitant branching factors [20].

Classic tree search methods were originally used to play simple board games such as Chess and Checkers and are unsuitable for high branching factors. Instead, the field of Game AI has successfully tackled this problem by using methods such as reinforcement learning, evolutionary algorithms and Monte-Carlo tree search [10].

Applying some (or all) of these methods to tackle the optimisation of the Global Calculator would contribute to the literature.

4. Libraries

Where possible, methods will be implemented from scratch. In addition to NumPy, Matplotlib and Pandas, a range of appropriate libraries are suggested:

- *Selenium* – Web scraping
- *Pytorch* – Machine learning
- *Scipy* – Constrained optimisation
- *PyMC3* – Markov Chain Monte Carlo

V. Preliminary Results

A. Lever sensitivity analysis

Users of the Global Calculator can choose up to 50 lever values, each ranging between 1 and 4.

To study the climate impact of each lever, a preliminary mono-parameter sensitivity analysis has been carried out. It shows the decrease in GHG emissions per capita that results from moving each single lever from level 2 to 3 (Fig. 1).

Inputs related to diet and land use yield the largest relative decrease in forecasted GHG emissions.

B. *Interacting with the Global Calculator*

A dataset has been generated to train the feed forward NN by logging random lever combinations and their corresponding outputs.

VI. Project Management and Schedule

A Gannt chart (Fig. 2) is used to track the timeline, progress and risks of this investigation. It includes a range of deliverables aimed at fulfilling the project objectives.

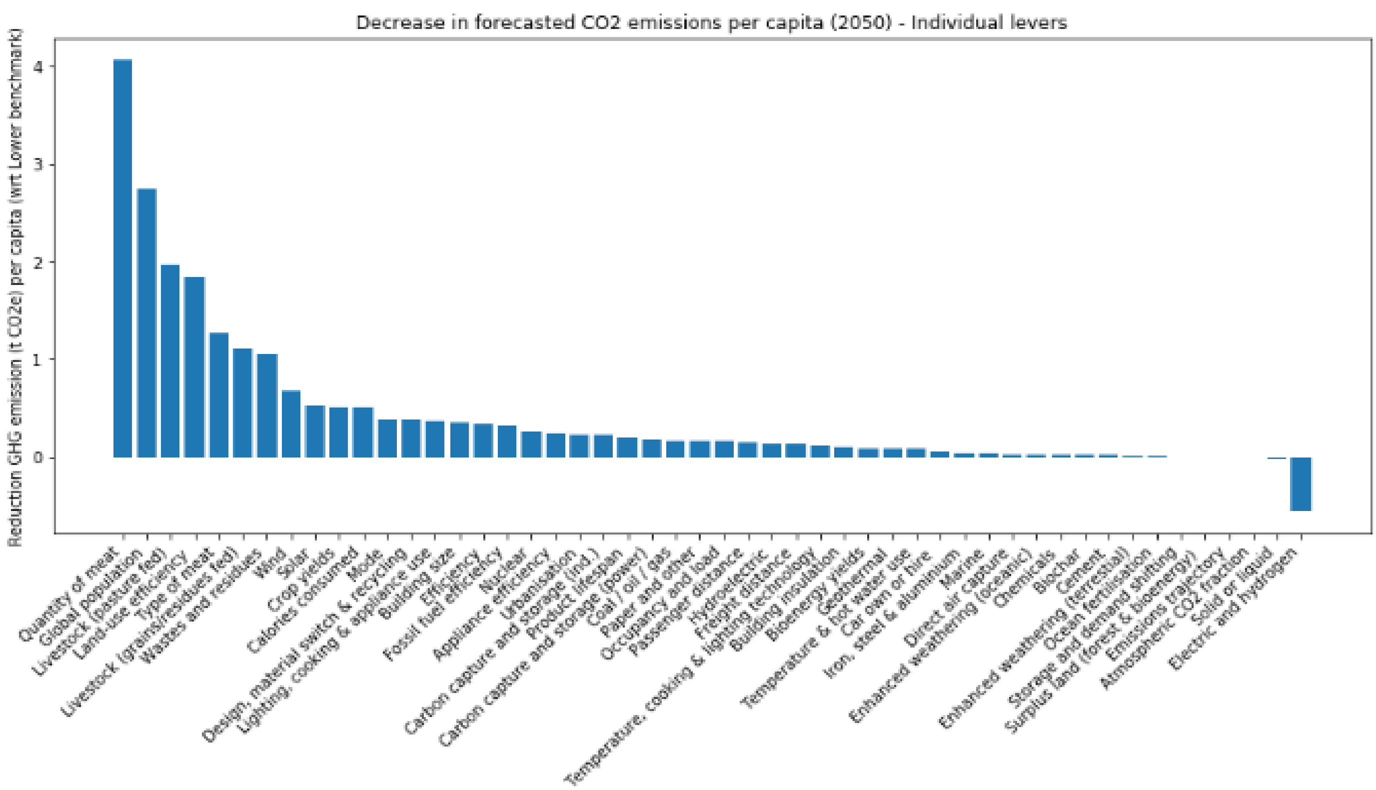

Fig. 1. Mono-parameter sensitivity analysis

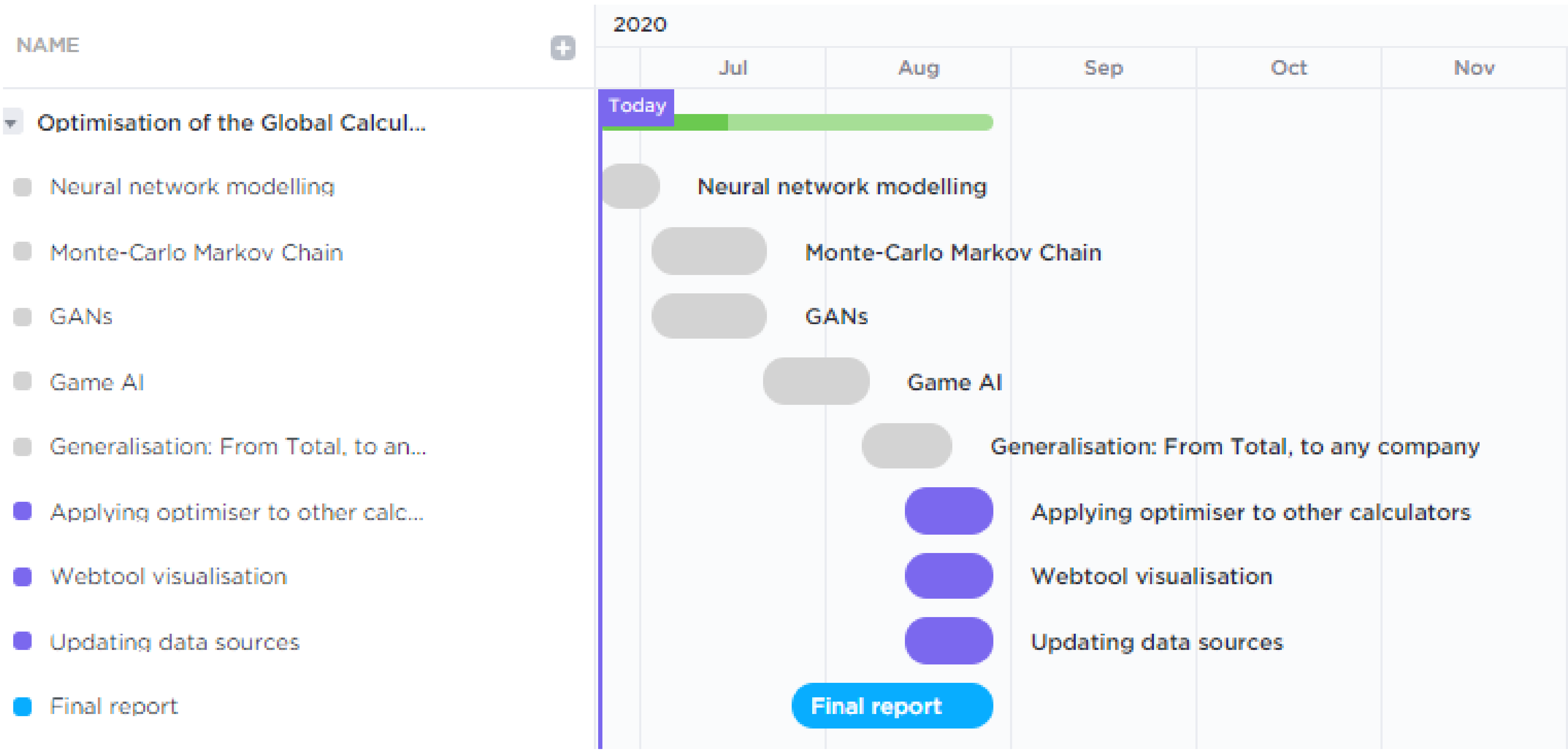

Fig. 2. Gantt chart

References

[1] "An early view on the results of the 2050 Calculator International Outreach", UK Department of Energy & Climate Science, 2015. [Accessed 24 June 2020].

[2] "Prosperous living for the world in 2050: insights from the Global Calculator", UK Department of Energy & Climate Change, 2015. [Accessed 24 June 2020].

[3] "The Global Calculator Sector metrics from 2°C pathways", UK Department of Energy & Climate Change, 2020. [Accessed 24 June 2020].

[4] A. Strapasson et al., "Modelling carbon mitigation pathways by 2050: Insights from the Global Calculator", Energy Strategy Reviews, vol. 29, p. 100494, 2020. Available: 10.1016/j.esr.2020.100494.

[5] A. Strapasson, J. Woods, H. Chum, N. Kalas, N. Shah and F. Rosillo-Calle, "On the global limits of bioenergy and land use for climate change mitigation", GCB Bioenergy, vol. 9, no. 12, pp. 1721-1735, 2017. Available: 10.1111/gcbb.12456.

[6] A. Elizondo, V. Pérez-Cirera, A. Strapasson, J. Fernández and D. Cruz-Cano, "Mexico's low carbon futures: An integrated assessment for energy planning and climate change mitigation by 2050", Futures, vol. 93, pp. 14-26, 2017. Available: 10.1016/j.futures.2017.08.003.

[7] "Editorial, Environmental Development, December 2019.", Environmental Development, vol. 32, p. 100471, 2019. Available: 10.1016/j.envdev.2019.100471.

[8] "United nations expert group meeting on population, food security, nutrition and sustainable development for sustainable development", United Nations Secretariat, Department of Economic and Social Affairs, 2019. [Accessed 24 June 2020].

[9] M. Bailera, P. Lisbona, S. Espatolero and L. Romeo, "Power to Gas technology under Spanish Future Energy Scenario", Energy Procedia, vol. 114, pp. 6880-6885, 2017. Available: 10.1016/j.egypro.2017.03.1828.

[10] G. Yannakakis and J. Togelius, Artificial Intelligence and Games. 2018.

[11] C. Jensen et al., "Inversion of feedforward neural networks: algorithms and applications", Proceedings of the IEEE, vol. 87, no. 9, pp. 1536-1549, 1999. Available: 10.1109/5.784232.

[12] S. Ferrari and R. Stengel, "Smooth Function Approximation Using Neural Networks", IEEE Transactions on Neural Networks, vol. 16, no. 1, pp. 24-38, 2005. Available: 10.1109/tnn.2004.836233.

[13] L. Shiyu and R. Srikant, "WHY DEEP NEURAL NETWORKS FOR FUNCTION APPROXIMATION?", Department of Electrical and Computer Engineering, University of Illinois at Urbana-Champaign, 2017. [Accessed 24 June 2020].

[14] J. Rogelj et al., "Paris Agreement climate proposals need a boost to keep warming well below 2 °C", Nature, vol. 534, no. 7609, pp. 631-639, 2016. Available: 10.1038/nature18307.

[15] A. Strapasson, J. Woods and A. Donaldson, "Bulb Calculator: An Independent Review", Report commissioned by Bulb Energy Limited, 2020. [Accessed 24 June 2020].

[16] R. L. Harrison, "Introduction to Monte Carlo Simulation", AIP Conference Proceedings 1204, 17, 2010. [Accessed 24 June 2020].

[17] C. Robert and G. Casella, "A Short History of Markov Chain Monte Carlo: Subjective Recollections from Incomplete Data", Statistical Science, vol. 26, no. 1, pp. 102-115, 2011. Available: 10.1214/10-sts351.

[18] A. Creswell, "Generative Adversarial Networks: An Overview", arXiv:1710.07035v1 [cs.CV], 2017. [Accessed 24 June 2020].

[19] I. J.Goodfellow, "Generative Adversarial Nets", Universite de Montreal - Departement d'informatique et de recherche operationnelle, 2017.

[20] S. Mohandas, "A.I for Games with High Branching Factor", 2018 International CET Conference on Control, Communication, and Computing (IC4), 2018. [Accessed 24 June 2020].