

Reinforcement Learning and Life Cycle Assessment for a Circular Economy - Towards Absolute Sustainability

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Abstract: We discuss the potential of using methods from reinforcement learning to achieve absolute sustainability in the economic system by respecting planetary boundaries. In the beginning, we present the “strategic triangle of AI” for such an ambivalent endeavor as an introduction. We then formulate the computer-science related challenges of changing the economic paradigm towards (absolute) sustainability, and in how far what we call ‘progressive computer science’ needs to contribute. Those challenges include the closing of material loops in a circular economy to optimize for (absolute) sustainability, and we present some new ideas in this direction. To give some context, we explain how reinforcement learning was successfully applied in computer chess and beyond (e.g. in AlphaZero / AlphaFold). Finally, we discuss the potential of such methods for ecological economic planning by changing the current mostly ‘linear’ and profit-driven way of organizing the economy towards a more circular, democratic and sustainable mode of production.

Keywords: Reinforcement Learning, Circular Economy, Life Cycle Assessment, Absolute Sustainability, Artificial Intelligence, Computer Chess, Strategic Triangle, Progressive Computer Science

1 Introduction - The Strategic Triangle of AI for Sustainability

Since a few years, there is a hype around “Artificial Intelligence” (AI), and the amount of digital data about products that is available increases steadily, including ecological data e.g. for so-called “life cycle assessment” (see e.g. [ZBT23]). We will have a closer look at the role that digital product data and AI (in a broad definition, see below) can play for sustainability. The focus will be on questions related to the economic system, such as those arising in order to “close the loops” of material flows and to achieve a “circular economy”.

Let us denote by “Big Tech AI” the currently dominant way that so-called “Artificial Intelligence” is organized and used, e.g. referring to the research of Cecilia Rikap, as outlined in her book “The Rulers: Corporate Power in the Age of AI and the Cloud” ([Ri25b]). Then, for the transition to an economic system that respects planetary boundaries and the role AI can play in it, we propose to map three different strategic aspects in the corners of a “strategic triangle”, namely “protest against how capitalism uses Big Tech AI”, “mitigation of the worst consequences of capitalist Big Tech AI” and “using the potential of AI for the transition to a sustainable (potentially post-capitalist) economy”. The last point includes evaluating options for democratic and ecological (computerized) economic planning, which we will discuss shortly at the end of this paper (see also [Bu25b; GS25; HZ24; Ri25a; Sa21; Sa24; Ze24]).

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The current hype of AI was fuelled by the introduction of large language models (“LLMs”) like ChatGPT, and nowadays “AI” and “LLMs” are often used interchangeably. However, for our purpose, AI can and should be defined much more broadly: A classic definition by Marvin Minsky from the 1960s defined AI as “the science of making machines do things that would require intelligence if done by humans”, and in a recent article on artificial intelligence and modern planned economies, Spyros Samothrakis noted that historic debates and proposals on computerised economic planning (CEP) “have been inspired by and/or have touched upon other numerate disciplines like cybernetics, game theory, optimisation, complex systems, machine learning, and statistics. Arguably, the applied cutting edge of the fields that have partially contributed to the debate is currently being studied under the broad umbrella of artificial intelligence (AI).” (see [Sa24], p.1).

The overall aim of this paper is to describe some methods that were successful in computer chess such as Reinforcement Learning ([Chb]), and to discuss their potential for solving problems in other domains, with a focus on sustainability. We note that since the introduction of AlphaZero ([Si17]) which was able to achieve superhuman performance in chess, trained only by reinforcement learning from games of self-play, similar approaches lead to spectacular success in other domains, e.g. the “other Alphas” (all created by DeepMind) like AlphaFold [Deb], AlphaTensor [Fa] and AlphaProof [Dea]. In this spirit, we propose some new ideas how to tackle the problem of closing of material loops in a circular economy in order to optimize for sustainability, which is part of a research program that we call “Progressive Computer Science” in order to respect planetary boundaries (see [Ro09]) and avoid climate tipping points [Ar22].

We now describe the structure of the paper a bit more in detail: The Section 2 following this Introduction is based on the (unpublished) paper [Bu25a]. It deals with reinforcement learning in computer chess and beyond, referring to FUSC#, which is the chess program that was developed by the “AG Schachprogrammierung” at the Free University in Berlin ([Cha]). For more background of FUSC#, see [BI05]. After briefly discussing AlphaZero and its sample efficiency, we review some application of the ideas developed in AlphaZero in other domains.

In the following part, we propose some new ideas how to tackle the problem of closing of material loops in a circular economy in order to optimize for sustainability. We also briefly discuss why this is urgently necessary to avoid climate tipping points [Ar22], and achieve absolute sustainability [HKR20]. There is growing scientific evidence that exceeding 1.5 °C global warming could trigger multiple climate tipping points. We are deeply convinced that these alarming facts from climate science necessarily demand research on what we call ‘Progressive Computer Science’, as computer science (as well as many other fields) urgently need to contribute to fighting the ecological crisis.

Finally we elaborate on the potential of artificial intelligence methods for (ecological) economic planning in order to achieve economic democracy within planetary boundaries, as outlined e.g. in [Sa21] or [Sa24].

2 Reinforcement Learning in Computer Chess and Beyond

2.1 The Paper “Reinforcement Learning in Chess Engines” (2008)

We quote from the introduction of the paper “Reinforcement Learning in Chess Engines” ([B108]) from 2008, where the state of the art at that time was discussed, based on experiments with FUSC#: “The method presented in this paper optimizes the evaluation functions and its coefficients by automating the use of temporal differences and thereby increasing it’s own understanding of chess after each game.” Back then, the idea was that “the main problem lies in the correct tuning of the coefficients” of the evaluation functions, and that only there Reinforcement Learning could play a useful role in chess engines, not during the search. In the “related work”-section of the same paper [B108], a paragraph on “NeuroChess” is interesting to read from the perspective of today: It states that, based on the experience with “NeuroChess”, experiments “showed that a learning strategy based on playing against oneself, does not yield satisfying results”, which was the common sense in 2008, but changed dramatically with AlphaZero, less that 10 years later.

2.2 The Approach of AlphaZero

In December 2017, a paper was uploaded to arxiv with the title “Mastering Chess and Shogi by Self-Play with a General Reinforcement Learning Algorithm” [Si17]. Its reinforcement learning algorithm, “starting from random play, and given no domain knowledge except the game rules, achieved within 24 hours a superhuman level of play”. So the game of chess was mastered “by tabula rasa reinforcement learning from games of self-play”, in contrast to what seemed possible a decade ago. The approach of AlphaZero is very different to classical chess programs and FUSC#: Instead of an “alpha-beta search with domain-specific enhancements”, it uses “a general-purpose Monte-Carlo tree search (MCTS) algorithm”. Each search consists of a series of simulated games of self-play that traverse a tree” from root to leaf (compare p.3 of [Si17]).

But to achieve this impressive result, millions of self-play training games were used for the training: About 20 million games (approx. 4 hours of training time) were necessary to achieve super-human performance, and about 44 million games (approx. 9 hours of training time) were necessary to beat Stockfish, the best available computer chess program at the time ([Si17]). We now collect some ideas how to improve “sample efficiency” (i.e. to reduce the number of training games necessary). In the “Conclusion”-Section of the 2008-paper, it is stated that FUSC# considerably improved performance only after 119 (!) games, and also “we estimate that FUSC# requires more than 50.000 training games ...” (p.9 of [B108]) - so in a way, there was a much higher “sample efficiency” (of course with limitations w.r.t the performance/chess playing strength, which peaked only at about 2000 ELO, which is “expert” level, but significantly below “grandmaster”). A promising strategy improve sample efficiency is to relate the “piece evaluation heuristics” to “position type”

(e.g. opening, middle game, endgame), because the former will greatly vary with the latter (e.g. “king safety” in the middle game vs. “active king play” in the endgame). At first such a structure could be “given”, but the aim is that a “FUSC#-Zero” will “re-discover” such “position-types” itself in a second step, maybe with even more “position types” that just 3 (according to [BI08], in FUSC# 33 were used).

2.3 The “other Alphas”

We review the application of the ideas developed in AlphaZero in other domains, i.e. the “other Alphas” (all created by DeepMind) like AlphaFold [Deb], AlphaTensor [Fa] and AlphaProof [Dea]. AlphaFold [Deb] had spectacular success applying the ideas of AlphaZero to predictions of protein structure. The most recent AlphaFold 3 was announced in May 2024, and it can predict the structure of complexes created by proteins with DNA, RNA, various ligands, and ions. Demis Hassabis and John Jumper of Google DeepMind shared one half of the 2024 Nobel Prize in Chemistry, awarded “for protein structure prediction” with AlphaFold (for more details see e.g. [Deb]). AlphaTensor [Fa] was developed to shed “light on a 50-year-old open question in mathematics about finding the fastest way to multiply two matrices”, and discovered new, faster algorithms to do so. AlphaProof and AlphaGeometry2 [Dea] solved four out of six problems from the 2024 International Mathematical Olympiad (IMO), achieving the same level as a silver medalist.

3 Absolute Sustainability, LCA and Progressive Computer Science

In this final part of the paper, we propose some new ideas how to tackle the problem of closing material loops in a circular economy in order to optimize for sustainability. To the best of our knowledge, we are the first to propose using methods that originate in computer game research (described in the previous section) to tackle such questions. We were heavily inspired by the work of Spyros Samothrakis (see [Sa21] and [Sa24]).

We start by briefly discussing why this is urgently necessary to avoid climate tipping points [Ar22], and achieve absolute sustainability [HKR20]. According to the “Global Tipping Points Conference” ([GI]), there is growing scientific evidence that exceeding 1.5 °C global warming could trigger multiple climate tipping points (see also [Ar22]).

3.1 Absolute Sustainability and Climate Tipping Points

Absolute sustainability aims to achieve a development that stays within the Earth’s environmental limits, ensuring both present and future generations can meet their needs while respecting the planet’s carrying capacity, according to [HKR20]. This means that the environmental impacts of our activities must be assessed (with “Life Cycle Assessment”,

see below) against established thresholds, such as planetary boundaries, to determine if they are truly sustainable, in an “absolute” sense (in contrast to “relative” sustainability where the question is e.g. “if product A is more sustainable than product B”, without reference to an “absolute” reference frame). Absolute sustainability thus focuses on staying within the safe operating space defined by planetary boundaries, which represent the limits of the Earth’s systems (see [Ro09]).

According to [Ar22], exceeding 1.5 °C global warming could trigger multiple Climate Tipping Points (CTPs). As the authors explain, “climate tipping points are conditions beyond which changes in a part of the climate system become self-perpetuating. These changes may lead to abrupt, irreversible, and dangerous impacts with serious implications for humanity.”. The paper synthesizes evidence for 16 core and regional-impact tipping elements and finds that exceeding 1.5 °C global warming could trigger multiple climate tipping points. As the authors conclude, assessment “provides strong scientific evidence for urgent action to mitigate climate change. We show that even the Paris Agreement goal of limiting warming to well below 2 °C and preferably 1.5 °C is not safe as 1.5 °C and above risks crossing multiple tipping points. Crossing these CTPs can generate positive feedback that increase the likelihood of crossing other CTPs. Currently the world is heading toward 2 to 3 °C of global warming; at best, if all net-zero pledges and nationally determined contributions are implemented it could reach just below 2 °C. This would lower tipping point risks somewhat but would still be dangerous as it could trigger multiple climate tipping points”.

3.2 Life Cycle Assessment and Circular Economy

The environmental impact of products can be traced with “Life Cycle Assessment” (LCA). One example is openLCA (see openlca.org), a free and open source software for modeling the life cycle of products and sustainability. For a broader discussion of Life Cycle (Sustainability) Assessment in the context of Societal-Ecological Transformation, see [ZBT23]. Clearly, a sophisticated LCA is necessary for absolute sustainability and for the closing of material loops in order to optimize for sustainability in a Circular Economy.

In order to promote a Circular Economy in Germany, the “National Circular Economy Strategy” (NKWS) was adopted in December 2024 ([Bu24]). In that context, the recently published survey paper “AI for the Circular Economy - a tool for sustainable transformation?” ([Le25]) underlines the important role Artificial Intelligence (AI) can play for such a transformation, if employed in the right places and within the proper context. However, it also states clearly that the creation of a sustainable economic system is not merely a “technical” question, but a political one, and that currently, the way AI is used has in many cases very bad consequences for the environment, e.g. related to energy use. As mentioned in the introduction, we propose a “strategic triangle of AI for sustainability” in order to capture those ambivalence, see also [Bu25b].

The fundamental problem of trying to understand how to transform the economy to be more “circular” requires moving from individual production processes to a more global view of the economy. We look at products and their pre-products, from an overall perspective in the economy (like with LCA-data), and observe that there are multiple ways of creating the same product. The aim is to choose the most “circular” and “sustainable” one in order to achieve absolute sustainability, which is a “global” question for the whole economy, as the choices on pre-products and production processes heavily depend on each other, and from a sustainability perspective, those choices will have economy-wide consequences. As a new approach, we propose to use state of the art methods from AI, Reinforcement Learning and Game Tree Search (e.g. Monte Carlo Tree Search that was successfully used in “AlphaZero”, see above) to investigate such questions. As a first step, we introduce some definitions in order to illustrate this idea and to describe the arising challenges more precisely.

Definition 1 (*Product*) A product p is a triple $p = (l, n, \{a_i\}_{i=1}^n)$, where $l \in \mathbb{N}$ stands for the “level” of the product, $n \in \mathbb{N}$ stands for the number of other pre-products it is composed of, and there is a set consisting of a_i defining those pre-products and the associated quantities:

$a_i = (q_i, p_i)$, where $i \in \mathbb{N}$ and $q_i \in \mathbb{R}$ stands for the quantity of product p_i that is needed to produce product p .

Remark 1 Note that this is a recursive definition, as the product p appears “on both sides”. Thus, we define “raw materials” as the seed:

Definition 2 (*Raw Material*) Let there be $\tilde{r} \in \mathbb{N}$ raw materials in the economy.

A “raw material product” is a product of “level 0”, i.e. $\text{raw} = p = (0, 1, (1, r))$ with $r \in \{1 \dots \tilde{r}\}$

Remark 2 By this definition, all products and intermediate “pre-products” can be tracked back to which raw materials they contain.

Definition 3 (*Life Cycle Assessment, LCA*)

Let there be $m \in \mathbb{N}$ different indicators for LCA measuring the impact of a product on the environment (and society).

For a product p , define its Environmental Impact over its lifecycle, as a tuple

$\text{lca}(p) = (b_j)_{j=1}^m$. For simplicity, and following [HZ24], we assume that only 3 indicators are measured for each product

- labor time t , i.e. the time necessary to produce p

- “climate cost” c , i.e. the amount of greenhouse-gases (e.g. CO_2 -equivalents) the production produces
- raw materials $r = (r_1, \dots, r_{\bar{r}})$ necessary to produce p

Remark 3 *In this simplified setting, it holds that for each product p_i we have*

$$lca(p_i) = (t_i, c_i, r_i)$$

Definition 4 *(Recursive Definition of LCA for a product)*

Let p be a product, with $p = (l, n, \{a_i\}_{i=1}^n)$ and $a_i = (q_i, p_i)$, i.e. p is composed of n pre-products p_i with $i = 1 \dots n$, as above. Then define the “environmental and societal impact” / “life cycle assessment” as

*$lca(p) = \sum_{i=1}^n q_i * lca(p_i) = \sum_{i=1}^n (q_i t_i, q_i c_i, q_i r_i)$, with the last step following from our “simplified setting” with only 3 indicators.*

Now we are in a position to formulate concrete challenges on how to close material loops in a circular economy and to find the most sustainable way to produce a product. In order to do so, we assume the following (making these assumptions more precise is part of the challenge to formulate the problem in a way that modern AI-methods can be implemented):

- Assume different “production processes” are defined, which result in products with the same “features”, but different environmental impact...
- ... which also means that products with the same “features” are composed by different pre-products, and the challenge is to find the most “sustainable” and “circular” way to produce all goods in the economy (the latter meaning that material loops are closed where possible, i.e. that the unused output/“waste” from one production process is used as “input” for as many production processes as possible).

Remark 4 *Let p be a product as above, and let $x := p_1$ be a pre-product of p . Assume that a new production process allows us to replace x by a new pre-product y , and denote this new product involving y by $\tilde{p}$. Then the environmental impact / LCA of p changes in the following way:*

$$lca(\tilde{p}) = lca(p) - lca(x) + lca(y)$$

Definition 5 *(Challenge: The Game of a Circular and Sustainable Economy)*

Observe that searching this “space of possibilities” for an economy with many such possible “pre-product replacements” has similarities with a search tree in computer games like chess, as discussed above. With this analogy in mind, define

- a “move” in the game of a “Circular and Sustainable Economy”: $\tilde{p} = \text{move}(p, x, y)$, i.e. such a “pre-product replacement” is considered a move in the game².
- as “evaluation function”, the environmental impact of all products produced in the economy needs to be calculated - and according to the principle of “absolute sustainability”, it must be within the “planetary boundaries”

Remark 5 Even “bitboards” that have been used successfully in many board games may play a role in this setting, because the “incremental update” of “sustainability bitboards” (which can be defined according to the concrete optimization question at hand) by bit-wise logical operations might save a lot of computing time, as with “classical” board games.

3.3 Progressive Computer Science

There are arguably many possible definitions of “Progressive Computer Science”, depending how “societal progress” is defined. Here, we put the focus on preserving the planet for future generations, as urgent action is necessary in order to avoid the climate tipping points and to respect the planetary boundaries, i.e. to reach absolute sustainability (see above).

Definition 6 (“Progressive Computer Science”)

We define “Progressive Computer Science” as an umbrella for research in computer science that contributes to transforming the economic system towards absolute sustainability. This involves changing the rules on how the economy works in a way that ensures that planetary boundaries are respected.

An example that falls in this category of “Progressive Computer Science” is research on ecological economic planning with computer science methods, which is the topic of the next section.

3.4 Ecological Economic Planning and AI

Recent developments in AI (e.g. in the field of reinforcement learning) have enabled economic planning at large scales e.g. in multinational companies (see e.g. Phillips and Rozworski (2019)). In the EU, a “Circular economy Action Plan” [Eu20] was adopted, and one central part of it is to improve the availability of digital product data. The “EU digital product passport” (see e.g. [Eu19] or [Eu22]) is designed to provide information about each product’s origin, materials, environmental impact, and disposal recommendations. With

² Note that this does not depend on any linear relationships, and that with this idea, also highly interdependent and non-linear structures in the economy can be captured.

this European-wide product data infrastructure for all products sold and used in the EU, new forms of ecological economic planning will become possible. For a recent discussion of such methods and institutions regarding Artificial Intelligence and economic planning, see [Sa21], for a broader perspective see [GS25] or [Ze24]. This opens up new possibilities to change the current mostly 'linear' and profit-driven way of organizing the economy towards a more circular, democratic and sustainable mode of production (see e.g. [HZ24] or [Sa24]).

Given the obvious complexity of organizing let's say the economy of the EU (ca. 450 million inhabitants), it is necessary to do fundamental research on how digital product data and AI can be used for economic planning. Even if 99% of the (about 600 million) products listed on amazon are useless and won't be produced in a post-capitalist economy, we are definitely looking at millions of products (and their pre-products) that more than half a trillion Europeans (if we look beyond the EU member states) would probably like to keep in some form even in a post-capitalist economy. But if "it is easier to imagine the end of the world than the end of capitalism", as a famous quote says, maybe the hype on AI can contribute to a hegemonic view that "technologically, a post-capitalist economy is possible", which could prove very helpful for political fight to transcend capitalism. We propose to use this dynamics for the purpose of popularising democratic and ecological economic planning for a post-capitalist circular economy.

Acknowledgments

The section on the closing of material loops in a circular economy in order to optimize for sustainability by using ideas in the spirit of AlphaZero is based on common discussions with Spyros Samothrakis, e.g. at a research stay in Essex in September 2024. We are deeply indebted to him for this inspiration; without it, this paper could not have been written. Also thanks to Christoph Sorg, Jan Groos, Eric Meier and other participants in the INDEP-network for introducing me to the recent discussion on the topic of democratic planning, as well as to Walther Zeug and the other members of the organizing committee of the workshop with the (German) title "KIT-KREIS: KI für die Transformation zur Kreislaufwirtschaft - Das strategische Dreieck" for many valuable discussions related to the subject of this paper.

Also note that a major revision of this paper has been accepted at the "EnviroInfo 2025" conference and will be published under the title "Rotated bitboards and Reinforcement Learning in Computer Chess and Beyond - Towards Absolute Sustainability and Progressive Computer Science" in the corresponding "Lecture Notes in the Informatics (LNI) - Proceedings"-series of that conference, which is the 39th edition of the long-standing and well-established international and interdisciplinary conference series on leading environmental information and communication technologies.

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