Green AI: How constraint based tools can be used for sustainability and for achieving the SDG objectives

Giuseppe Morgese

July 1, 2022

Contents

1 Introduction

The Sustainable Development Goals (SDGs) were introduced in the United Nation's 2030 Agenda [2] as a set of 17 goals divided in 169 targets to build a better and more sustainable world.

In [9] the impact of Artificial Intelligence on SDGs is discussed. The goals are divided in three categories: Environment, Society and Economy. The kind of evidence was taken into account in order to weight links between AI and targets. Clearly references with stronger scientific methods contributed more. AI may act both as an enabler or an inhibitor for a given SDG thus the reported percentages often overlap.

The impact of AI on single SDGs is reported in Table 1. The "+" indicates the percentage of targets for which AI may act as an enabler. Intuitively, the "-" indicates the percentage of targets for which AI may act as an inhibitor. "N/A" shows the percentage of targets for which evidence was not available.

Table 2 shows the results on each category and on the totality of SDGs.

The results of the paper show that AI can be used to achieve SDGs as long as negative impacts are considered and addressed.

	Environment			Society									Economy				
SDG	13	14	15	1	2	3	4	5	6	7	11	16	8	9	10	12	17
+	70%	90%	88%	100%	69%	69%	93%	44%	100%	100%	90%	52%	77%	91%	75%	59%	15%
-	20%	13%	8%	43%	13%	8%	60%	31%	28%	40%	10%	15%	25%	34%	55%	16%	5%
N/A	20%	10%			25%	31%		44%				42%	8%		10%	18%	68%

Table 1: Impact of AI on single SDGs

	Environment	Society	Economy	Total
Positive impact	85%	77%	55%	71%
Negative impact	12%	25%	23%	23%
Data not available	7%	18%	28%	20%

Table 2: Impact of AI on categories of SDGs

2 AI for sustainability

In this section some cases in which AI helps achieving sustainability are analyzed.

2.1 Some examples of sustainable AI applications

[6] provides an example of application of different AI techniques in the process industry in order to achieve Green manufacturing. The three main objectives to keep in mind for this purpose are:

1. reduction of energy consumption and pollutant emissions
2. life-cycle process-safety monitoring and risk control
3. environmental footprint monitoring and evaluation

Green manufacturing uses smart monitoring, intelligent decision-making, optimization-based pollution reduction techniques and intelligent early-warning in order to track safety-related aspects. The techniques considered to achieve this goal include Knowledge graphs, Bayesian networks and Deep learning.

Besides the single advantages brought by the usage of AI alone, it's important to consider the benefits given by the combination with other technologies such as Internet of Things (IoT).
In fact, as outlined in [7], the cooperation between supply chain components can be improved exploiting the synergy between IoT technology and artificial intelligence in such a way as to obtain rapid transfer and distribution of accurate real-time information in order to increase the efficiency of the supply chain.

These hybrid solutions can play a major role in improving environmental conditions. As a matter of fact the paper shows how Artificial Intelligence of Things (AIoT) is an enabler for green supply chain management with an environmental management approach which permits a closed loop of material flow (raw material preparation, design, construction, use and recycling, reuse) in order to reduce resource consumption and lower the harmful effects on the environment.

Another application of AIoT regards transportation networks. IoT collects real-time data in a simple way and analyzes them so as to achieve traffic patterns and parking availability, reduce gas consumption and greenhouse gases use. In this way, the goals of the transportation network could be achieved, which would increase safety, satisfy passengers and solve the problem of traffic and congestion which would reduce CO_2 emissions.

Some other reasons to use AIoT in Supply Chain Management are:

- Real-time shipment location tracking
- Monitoring of the products' storage status during shipment
- Product movement predicting
- Selection of the best warehouse for a given item
- Improving potential planning

Regarding the last point of the list, AIoT helps manager of an intelligent supply chain to fulfill environmental laws and emissions restrictions. In fact, they can get an overview on how resources such as water and electricity are being used and can implement green strategies consequently.

These are only few of many opportunities made possible by AI techniques.

2.2 Constraint-based tools for sustainability

Amongst the fields of application, the one that plays a major role in greenhouse gases (GHG) emissions is supply chains. Indeed transportation and industry represent respectively 27% and 24% of the emissions in the United States [1]. Even in the European Union [5] those are among the major sources of emissions. The main enablers for sustainable supply chains are constraint-based tools. Two use cases are analyzed in the following subsections.

2.2.1 Bio-based production

As stated in [3], long distance transport result in higher logistics costs, energy consumption and GHG emissions compared to small-scale utilization. This means that the logistics networks of supply chains must be re-designed to reduce the environmental impact. The methodologies presented in the paper aim at providing the optimal supply chain configuration and transportation network design so as to identify cost-efficient bio-based supply chain with small environmental impact. Specifically, *"a bi-level Decision Support System (DSS) is developed to optimize multi biomass based supply chains and transportation networks under co-modality considerations to produce multiple types of bio products by different technology options in the same supply chain"*. In the first level of the DSS the optimum structure of the supply chain and the most appropriate production technologies under demand and feed stock availability limitations are selected. Given the results from the first step related to locations of nodes and the delivery amounts between the nodes, in the second step a model is developed to decide how optimally route the material flows from its origin to destination.

In order to obtain optimized solutions, the authors propose a hybrid algorithm that combines fuzzy logic and ϵ-constraint method in such a way as to address both sustainability aspects and system-specific uncertainties in the same framework. The use of fuzzy logic is justified by the fact that due to special and dynamic characteristics of energy problems, in some cases there might not be enough data to model uncertain parameters within each scenario. Fuzzy logic allows to develop robust approaches for concept representation of energy systems and supply chains with uncertain data.

To implement the bi-level DSS, two MILP (Mixed-Integer Linear Programming) models have been developed. The first one, the supply chain configuration design model (CDM), designs the biomass-based supply chain taking into account three elements:

1. configuration of the supply chain network
2. procurement and allocation of the biomass resources
3. inventory, production and distribution planning, while meeting the bio-product demand of a particular area

The outputs of CDM are passed to the second model, the transportation network optimization model (TNM). The CDM decisions determine the optimum locations of plants and facilities, conversion technology/facility types and capacities of plants and facilities. Whilst the TNM decisions are made considering the distances and material flow amounts between these specified locations. The TNM optimizes the biomass and bio-product distribution network and transportation mode considering that single mode and multi-modal transportation options (rail-road, road-sea, rail-sea, etc.) are available.

Methodology:

The ϵ-constraint method transforms a multi-objective optimization problem into a single-objective optimization problem minimizing only one objective function (the one considered most important) and using the other objective functions as constraints limiting them by some allowable values ϵ_i, $i \in \{1, ..., m\}$.
Below the classic structure of a multi-objective optimization problem is shown:

$$
\begin{aligned}
&max/min \quad (f_1(x), f_2(x), ..., f_m(x)) \\
&st \quad x \in S
\end{aligned}
$$

applying ϵ-constraint method to the problem above, a new one is obtained:

$$
\begin{aligned}
&max/min \quad f_1(x) \\
&st \; f_2(x) \geq \epsilon_2 \quad \textit{for max functions,} \\
&\quad f_3(x) \leq \epsilon_3 \quad \textit{for min functions,} \\
&\quad ... \\
&\quad f_m(x) \leq \epsilon_m \\
&\quad x \in S
\end{aligned}
$$

The efficient solutions of the problem are obtained introducing the ranges ϵ_i of objective functions. These ranges need to be calculated over the efficient sets. For this purpose, the hybrid solution uses fuzzy logic to determine the ranges considering the system uncertainties. Another issue with this method is that some of the generated Pareto solutions may be inefficient. Thus the most efficient solution amongst them must be selected. For this reason, the degree of optimality μ_k found through fuzzy logic is used.

To avoid dwelling on the matter, the more specific formulas are not reported. On the contrary, the results of the case study in the West Midlands region (UK) are considered worth showing.

Results:

The membership function μ_k values are based on three different weight structures for the objective functions giving each of them more or less importance:

1. $w_{profit} = 0.6$, $w_{emissions} = 0.2$, $w_{ton-km} = 0.2$
2. $w_{profit} = 0.2$, $w_{emissions} = 0.6$, $w_{ton-km} = 0.2$
3. $w_{profit} = 0.2$, $w_{emissions} = 0.2$, $w_{ton-km} = 0.6$

This results in three different scenarios, for each one only the best solution is selected for both CDM and TNM. The results of each stage of the decision making process are reported in Table 3 and Table 4.

Scenario	Monthly profit	GHG emissions	Transp. distance
1. max profit	€ 66361	2354048 Kg CO_2 eq	862845 ton-km
2. min emissions	€ 21070	2542 Kg CO_2 eq	974688 ton-km
3. min transp. distance	€ 34256	2648 Kg CO_2 eq	270766 ton-km

Table 3: CDM results

Scenario	Transp. costs	GHG emissions	Transp. time
1. min costs	€ 336446	118346 Kg CO_2 eq	478 min
2. min emissions	€ 448748	105266 Kg CO_2 eq	448 min
3. min transp. time	€ 448748	105266 Kg CO_2 eq	448 min

Table 4: TNM results

The solution chosen by the authors to feed the second step of the DSS is the one of the first scenario. This means that data in Table 4 refer to the profit scenario and could be replaced by the emissions one obtaining much more significant results from an environmental point of view. As it can be observed in Table 4, the second and third scenario gave the same solution in the second stage. Furthermore, it is important to specify that, if the environmental impact is considered the most important criteria, the model adopts single mode rail or multi-modal transportation depending on the available options between locations.

2.2.2 Wine industry in Australia

Another interesting example of application of constraint-based sustainability is given in [8]. In this case the model is formulated as a multi-objective mixed-integer program (MIP). Reporting the complex problem statement would be too long and would be beyond the scope of the report anyway. Thus, from now on, only interesting features will be specified. With a view to sustainability, three objective functions are defined:

1. Economic objective: minimize supply chain fixed and variable costs
2. Environmental objective: minimize GHG emitted by the transportation activities between suppliers, wineries, bottling plants, distribution centers and demand points
3. Social objective: maximize social sustainability of the supply chain network in terms of a set of social categories such as employment or impact on regions. The social aspects could influence the selection decision variables of the model. They can be incorporated as the coefficients of the selection decision variables

The use case involves three different transportation modes with different emission factors associated: Road, Rail, Sea.
Furthermore, unemployment and regional gross domestic product (GDP) associated with the location of bottling plants are considered to measure the social impact of the supply chain network. These categories are used to determine social coefficients representing the social impact of locating a new facility. Based on these scores, social coefficients are normalized on three bottling plant capacity options.

Methodology:

The paper presents a very detailed generic model for sustainable supply chain network design and adapts it on the use case to obtain a customized model. It utilizes three types of decision variables: binary, flow, auxiliary.

Differently from the already described ϵ-constraint, the augmented ϵ-constraint method generates only non-dominated solutions. It is fed by a priority list of objective functions and a number of grid points representing each objective required to construct an approximation to the Pareto front. With respect to the traditional ϵ-constraint method, the augmented one avoids redundant iterations thus achieving better computational performance. Specifically, it performs several steps: Firstly it computes a payoff table comprising the ranges of the objective functions over the efficient set. It optimizes the objective function of greatest priority first, obtaining the optimal value $f_1(x) = z_1^*$. Then it uses $f_1(x) = z_1^*$ as an additional constraint to optimize the second objective function. The method proceeds in the same way until it optimized every objective function.

Results:

The payoff table is constructed by performing several rounds of computations where a different objective for each round is prioritized. Table 5 shows the different solutions. The percentages represent the variation with respect to the current solution.

The authors assume that the economic objective would be considered as priority. Therefore the S2 scenario is selected. Table 6 focuses on the comparison between the economic and environmental scenarios.

The comparison does not justify properly the choice of the economic scenario rather than the environmental one given that against a modest increase in costs

Scenario	Cost [mln AUD per year]	Emissions [tonnes per year]	Social impact
S1. current solution	44,60	4936	0,667
S2. min cost	37,53 (-15,85%)	2215 (-55,13%)	0,778 (+16,64%)
S3. min emissions	38,66 (-13,32%)	1780 (-63,94%)	0,845 (+26,69%)
S4. max social impact	47,29 (+6,03%)	7151 (+44,87%)	0,967 (+44,98%)

Table 5: Solutions

Scenario	Cost [mln AUD per year]	Emissions [tonnes per year]	Social impact
S2. min cost	37,53	2215	0,778
S3. min emissions	38,66 (+3,01%)	1780 (-19,64%)	0,845 (+8,61%)

Table 6: Comparison between S2 and S3

(+3,01%), the environmental (-19,64%) and social (+8,61%) benefits are well worth the expense.

3 Sustainability of AI

As highlighted in [4], various AI technologies have extensive environmental costs. The production, usage and disposal of these technologies exhaust scarce resources, increasing the energy spent in their use and intensifying waste and pollution problems. Several AI technologies rely on data centers that require staggering amounts of energy to work on data with severe repercussions for the climate emergency.

Very often the environmental impact of AI is not accounted for when discussing and developing new policies on AI.

The paper displays some comparisons to better represent the urgency of the matter as shown in Table 7.

In addition to those already mentioned, further concerns regard, amongst others, water consumption of data centers cooling systems, energy consumption of AI models after training and electronic waste generated once communication and computational devices are discarded.

Brevini suggests a "Tech Carbon Footprint Label" to offer a transparent account of the carbon footprint of AI-powered solutions and to raise awareness and inform regulators and the public about it.

In [10] shortfalls in current AI conceptualization and practice are highlighted and a new approach that focuses on long-term ethical and sustainable AI practice, rather than on short-term efficiency solutions, is proposed. The current approach mainly aims for pure profit leading to increasing social inequality. As shown previously in [3] and [8], even when AI solutions target sustainability, they are mostly used to

AI technique/technology	Emissions/Consumption	Comparable to
a NLP training model	> 284 tonnes of CO_2	5x lifetime emissions of the average American car
cloud computing	energy cons. rate	Japanese and Indian national energy markets cons.
data centers	200 TWh yearly on average	> national energy cons. of Iran
digital technologies	energy cons.: +9% a year 3.7% of global GHG emissions	almost 2x aviation industry emissions

Table 7: Comparisons

improve business efficiency and economic productivity.

The authors introduce the concept of ”green sensing” as physical and virtual methods and technologies to measure environmental, social and economic sustainability. These should be green in terms of efficiency and energy usage. Specifically, some examples of green sensors are a physical sensor measuring pollution or the use of big data to detect road congestion (virtual green sensor). Thus these sensors may measure the impact of phenomena directly or indirectly.

Moreover, some techniques to save even further energy should be applied such as duty cycling, sensor selection or scheduling, adaptive sampling and so on. This would not only reduce the energy required for sensing but would also prevent meaningless data gathering.

The use of fog and edge computing based solutions would lower data transfer and bandwidth requirements of many applications by processing data locally while offering other advantages such as data security.

4 Conclusions

The effectiveness of artificial intelligence and especially constraint-based tools in achieving the SDGs mainly depends on the willingness to use them for that purpose. With reference to the main cases seen previously in sections 2.2 and 2.3, the goodness of results and utility of AI in the environmental field mainly depends on choices and priorities: environmentally convenient scenarios must be chosen over economically convenient ones.

The already analyzed cases could be improved using the data collected through the IoT. For example, a real-time DSS could be realized to eventually recalculate the solutions from time to time.

At the same time, the negative impact of AI needs to be considered and addressed thus requiring a different approach as stated in section 3.

References

[1] United States Environmental Protection Agency. Sources of greenhouse gas emissions, 2020.

[2] UN General Assembly. Transforming our world : the 2030 agenda for sustainable development. *A/RES/70/1*, 21 October 2015.

[3] Şebnem Yılmaz Balaman, Aristides Matopoulos, Daniel G Wright, and James Scott. Integrated optimization of sustainable supply chains and transportation networks for multi technology bio-based production: A decision support system based on fuzzy ε-constraint method. *Journal of cleaner production*, 172:2594–2617, 2018.

[4] Benedetta Brevini. Black boxes, not green: Mythologizing artificial intelligence and omitting the environment. *Big Data & Society*, 7(2):2053951720935141, 2020.

[5] European Commission. How are emissions of greenhouse gases in the eu evolving?, 2019.

[6] Shuai Mao, Bing Wang, Yang Tang, and Feng Qian. Opportunities and challenges of artificial intelligence for green manufacturing in the process industry. *Engineering*, 5(6):995–1002, 2019.

[7] Javid Ghahremani Nahr, Hamed Nozari, and Mohammad Ebrahim Sadeghi. Green supply chain based on artificial intelligence of things (aiot). *International Journal of Innovation in Management, Economics and Social Sciences*, 1(2):56–63, 2021.

[8] Mohsen Varsei and Sergey Polyakovskiy. Sustainable supply chain network design: A case of the wine industry in australia. *Omega*, 66:236–247, 2017.

[9] Ricardo Vinuesa, Hossein Azizpour, Iolanda Leite, Madeline Balaam, Virginia Dignum, Sami Domisch, Anna Felländer, Simone Daniela Langhans, Max Tegmark, and Francesco Fuso Nerini. The role of artificial intelligence in achieving the sustainable development goals. *Nature communications*, 11(1):1–10, 2020.

[10] Tan Yigitcanlar, Rashid Mehmood, and Juan M Corchado. Green artificial intelligence: Towards an efficient, sustainable and equitable technology for smart cities and futures. *Sustainability*, 13(16):8952, 2021.