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

Giuseppe Morgese

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

2.1 Some examples of sustainable AI applications

Mao et al. provide 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 **AIoT**, 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 of 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 29% and 23% of **the emissions in the United States**. The main enablers for sustainable supply chains are constraint-based tools.

As stated in **Bio**, 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.

2.2.1 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 shown.

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

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 1 and Table 2.

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 1: CDM 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 2 refer to the profit scenario and could be replaced by the emissions one obtaining much more significant 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 2: TNM results

from an environmental point of view. As it can be observed in Table 2, 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.

2.3 Wine industry in Australia

Another interesting example of application of constraint-based sustainability is given in **WINE**. 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 our scope 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 model utilizes three types of decision variables: binary, flow, auxiliary. PLACEHOLDER PLACEHOLDER PLACEHOLDER PLACEHOLDER

1. generic model (very big, don't think is a good idea rewriting it entirely)
2. 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
3. (don't know if i should use tables 1,2,3,4 or not. I'll think about it)
4. customized model (pretty big, don't know if it's a good idea rewriting it entirely)
5. describe augmented ϵ-constraint method: differently from the already described ϵ-constraint one, this 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.

6. (there are some optional bits describing the method, I'll evaluate if reporting them is useful or not)

7. Results: i think that my notes should be enough

3 Sustainability of AI

4 Conclusions

4.1 How to add Citations and a References List

You can simply upload a `.bib` file containing your BibTeX entries, created with a tool such as JabRef. You can then cite entries from it, like this: [Gre93]. Just remember to specify a bibliography style, as well as the filename of the `.bib`. You can find a video tutorial here to learn more about BibTeX.

If you have an upgraded account, you can also import your Mendeley or Zotero library directly as a `.bib` file, via the upload menu in the file-tree.

References

[Gre93] George D. Greenwade. The Comprehensive Tex Archive Network (CTAN). *TUGBoat*, 14(3):342–351, 1993.