Dynamic and Localized LCA Information Supports the Transition of Complex Systems to a More Sustainable Manner Such as Energy and Transport Systems

Florian Ansgar Jaeger, Cornelia Sonntag, Jörn Hartung, and Katrin Müller

Abstract The paper gives a snapshot of the potential of LCA (life cycle assessment) data-based optimizations in control systems. The environmental burden of existing infrastructure can be significantly reduced during use phase. Four Siemens' applications in different fields with different lead indicators show how LCA assessments can be adapted to fulfil the requirements of such applications. The applications are power and air quality management use cases in the field of eMobility, building management, industrial process control and traffic management. The main methodological challenge solved is the provision of the necessary temporal and special resolution, as well as forecasting of parameters for scheduling of processes.

1 Introduction

Life cycle assessment (LCA) methodology has become common to assess products and services and even found its way into strategy processes of planning infrastructure to convert our cities into sustainable urban areas [1]. Infrastructure has very long life cycles. Our time to cope with global warming is running up quickly, and there is little doubt that we need to speed up our climate actions as humanity. But to reduce emissions in markets with long life cycles, where inefficient assets can't quickly be replaced with sustainable ones, proves slow. We therefore propose to use LCAs of infrastructure during operation to improve the environmental performance of these infrastructures. To integrate environmental target functions into control systems and reducing or shifting consumption can increase environmental performance compared to conventional, solely monetarily or functionally optimized control algorithms. The goal is to make LCAs fit for control systems.

F. A. Jaeger (✉) · C. Sonntag · J. Hartung · K. Müller
Siemens Corporate Technology, Research in Energy and Electronics, Energy Systems, Sustainable Life Cycle Management and Environmental Performance Management, Berlin, Germany
e-mail: florian_ansgar.jaeger@siemens.com

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2 Four Applications

The four case studies used as examples to show the potential of embedding environmental target functions into control systems are building, energy and transport cases:

- Smart charging for bus depots: A use case using flexibility in charging time of buses during their stay in bus depots in order to charge at times, where the grid mix has low average emissions. The analysis is part of the Mobility2Grid project and funded by the German Ministry for Education and Research.
- Smart cooling: A campus air conditioning system, which uses an ice storage in order to shift power consumption for cooling aggregates to times, where the grid mix has low average emissions. The analysis is part of the EnBA-M project and funded by the German Federal Ministry for Economic Affairs and Energy.
- Smart chemistry, methanol from steel mill gases: A case study using flexibility in power consumption, making an otherwise highly emitting process reduces GHG emissions. The analysis is part of the Carbon2Chem project and funded by the German Ministry for Education and Research.
- City Air Management: An online service operative in Nuremberg which is used to forecast events of high air pollution on a 5-day horizon at a street site measurement station. It simulates different interventions for this period to select them at times of maximum efficiency.

The methods described are a combination of conventional LCA, executed in LCA software and conventional control systems including forecasting algorithms and optimization algorithms. From a pure LCA prospective, they are based on comparative LCA, since the optimizer, no matter if machine or human operator, has to select between different scenarios. Not all assessments cover the full life cycle.

3 Smart Charging for Bus Depots

To guarantee operations of electric bus depots, charging infrastructure is slightly oversized in order to compensate for high demand events such as very cold or hot weather, delayed buses, maintenance and many other inconveniences. This necessary flexibility creates times at which buses are not charged and the grid connection is not fully utilized. This case study is an ex post analysis of the potential of this flexibility to reduce carbon emissions by charging at times, where the grid provides power of low CO2e emissions. Three scenarios are analysed:

- Plug and charge: The buses are connected to the charger and start charging at full power, as soon as they are parked after returning to the depot and going through their daily routine.
- Cost-optimized: The buses are charged at max. Power during the period where the cost for power at the day-ahead market is the lowest without exceeding the grid connection.

- GHG-optimized: The buses are charged at max. Power during the period where the average GHG emission per kWh is the lowest without exceeding the grid connection.

The energy demand and schedules of the bus operation are based on real data from 140 Berlin diesel buses. Due to range restrictions, many buses are assumed to opportunity charge on the route. This increases the flexibility in depots.

3.1 Method

All three scenarios have the same hardware requirements, which is why only the power consumption during operations is part of the assessment. Only bidirectional charging or regulating the charging power based on battery wear would result in the necessity of expanding the system boundary to include the battery production and end of life. To calculate the optimum charging times based on an economic and a GHG target function, dynamic prices or emission functions for power are necessary. The spot market provides economic cost. Taxes and T&D (transmission and distribution) are not included. The dynamic country-based GHG emission factors per kWh are calculated on a time resolution of 15 min for Germany. T&D and upstream emissions are included. The grid mix is known for this time resolution, and each share of each energy carrier is multiplied with its respective energy carrier, as common for annual emission factor aggregates for countries too.

Combined with the bus schedules, dynamic emission factors feed into an optimizer, which defines at which time the buses are charged. The optimizer is set to optimize according to the target functions of the three scenarios stated above (view Fig. 1 Optimization Problem). The secondary constraints are the times the bus is available for charging, 100% state of charge when leaving the depot, the charging power and the grid connection limit of the depot. GHG emissions and cost for power are added up according to the resulting charging schedules of the three scenarios.

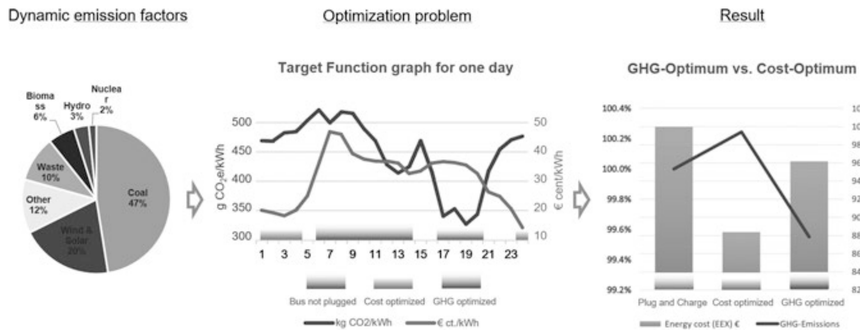


Fig. 1 Smart charging use case process

3.2 Results

The results show that the cost-optimized charging schedule does reduce the cost for power purchase at the energy market by almost 12% compared to a non-optimized plug and charge scenario. This results in a small increase in GHG emissions per kWh. The GHG-optimized charging schedule reduces GHG emissions by less than 0.5% and reduces cost by 4% compared to the plug and charge scenario (Fig. 1 on the right, GHG optimum vs. cost optimum).

3.3 Interpretation

The flexibility to shift charging times of buses is small. The shifting is only possible in the range of a few hours at maximum. The flexibility is almost exclusively available at night. There is almost no flexibility during daytime. But GHG emissions of the German grid mix don't frequently change drastically in short periods during the night, since there is no PV (photovoltaic power) at night and low-pressure zones for wind are moving slowly. This combination results in a marginal GHG saving potential of this application. In order to facilitate cost savings, however, the flexibility is relevant. Power prices at the power markets change more quickly at night, since the demand side has a larger impact. Cost-saving algorithms don't necessarily reduce GHG emissions as to be seen when looking at the results of the cost-optimized scenario.

4 Smart Cooling

Air conditionings are flexible loads. They are rarely running on full power, and any building has a certain thermal inertia, which can be used to store thermal energy. For this project, the thermal storage for the air conditioning was increased by adding a large ice storage to the system. The ice storage increases the temporal flexibility for power consumption. It can be charged independent of the demand of the building and discharged independent of the heat pump. This allows load shifting to provide similar services as smart charging. But in this case, the flexibility is much larger in the sense that power consumption can often be delayed or consumed ahead of time for several days. Additional complexity is added to the system compared to battery charging. The COP (coefficient of performance) and therefore the efficiency of the system differ significantly depending on the spread between the ambient temperature and the temperature of the thermal storage. These two parameters, plus the losses of the storage at high spreads over time, impact the overall power demand of the system. Since this system sets schedules in operation, the optimization is based on forecasted parameters for weather, power cost and emissions. The three scenarios and control mechanisms tested were similar to the smart charging case:

- Reference Scenario: System running without making use of the storage.
- Cost-optimized: The ice storage is filled at times with the best ratio of low power cost and high COP.
- GHG-optimized: The ice storage is filled at times with the best ratio of low relative GHG emissions for power and high COP.

As an additional indicator, the overall electricity demand is plotted.

4.1 Methodology

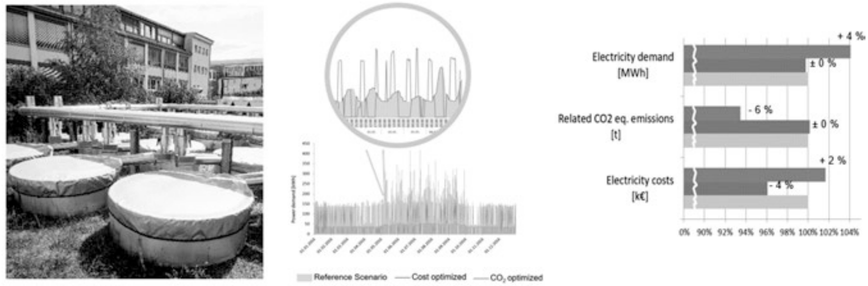
Even though the ice storage is not necessary for the operation according to the first scenario, production and end of life of the storage are not assessed. The storage was already available, but not in use, since cheap night rates for power had been abolished. The methodology of generating the environmental cost functions is the same as for bus charging above. But the data is based on forecasts for ambient temperatures, cooling demand of the buildings, cost and GHG emissions per kWh. The weather forecast is a commercially available API, and the other parameters are forecasted based on historical data of cooling demand and power generation mixes and day-ahead forecasts on renewable power generation and electricity load on the grid.

4.2 Results

Cost- and GHG-optimized operations are compared with the reference scenario. The cost-optimized operation shows a little reduction in power consumption of 0.2%, the GHG emissions increase by the same amount and the cost for power reduces by 4% (only cost at the power market). The GHG-optimized operation increases power consumption by 4% but reduces GHG emissions by 6%. Cost for power increases by almost 2% compared to the reference operation (Fig. 2: On the right).

4.3 Interpretation

It appears contradictory that the GHG-optimized operation leads to a higher power consumption. Figure 2 shows in the magnifier in the middle that the GHG-optimized operation leads to high power consumption in the middle of the day. This is due to the high availability of PV. The PV drives down the relative GHG emissions of the power mix at noon. This overcompensates the poor COP at daytime where ambient



Ice storage, Center of Photonic and Optics, Berlin

Load management for cooling managed by price or CO_2 target function.

6% carbon savings @ 2% higher cost

Fig. 2 Smart cooling use case process

temperatures are high and the temperature spread between the ice storage and heat exchanger outside is high. Power cost is more demand driven; thus, cost can also be low at night, where the COP is more favourable. The case shows once again that cost- and GHG-optimized operations can lead to opposing results and create conflicts of interest.

5 Smart Chemistry, Methanol from Steel Mill Gases

The concept of carbon capture and use is to use CO_2 emissions from industrial processes and to reduce them with hydrogen in order to create basic chemicals such as methanol. This project uses electrolysis of water for the production of hydrogen. The target is to draw power when the load on the grid is lower than production in order to minimize curtailment of electricity from renewable energy sources. Using the fossil-based methanol production process as a benchmark, it was determined that, in addition, the power for electrolysis has to stay below 0.2 kg CO_2 eq./kWh with its GHG emissions to generate carbon savings.

5.1 Methodology

The methodology in use is very similar to the first two applications. Since it takes a long time to set up such a large-scale system, forecasting becomes inevitable even to determine the environmental performance of the first year of operation. A power scenario with an hourly resolution with times and volumes of excess energy is created in a multi-model scenario approach. It is based on publicly available plans and policies for the development of installed capacities of German power plants by energy carrier and the net structure in 2030, combined with appropriate

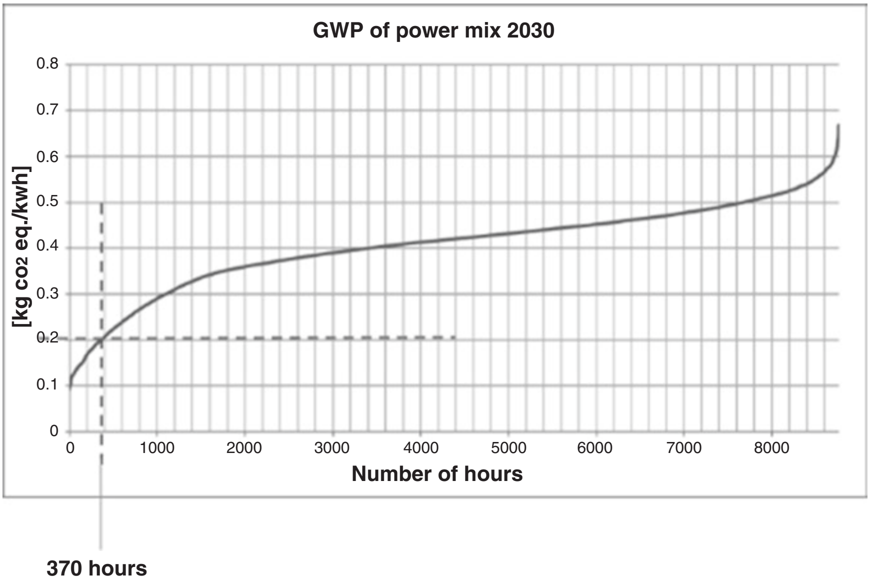


Fig. 3 GWP distribution of power

meteorological data. For the resulting power production profile, the greenhouse gas intensity of power production is calculated on an hourly base.

5.2 Results

For the underlying assumptions regarding the share of installed renewable energy sources, which results in a share of 47 per cent on gross power production, only 370 hours per year fulfilled the criteria of being below 0.2 kg CO_2 eq./kWh (Fig. 3). During these 370 h, the share of renewables in the power mix accounts for at least 70 per cent (Fig. 4). All these time periods coincide with periods of excess energy.

5.3 Interpretation

The analysis indicates that for the underlying assumptions on the share of renewables in power production, only few operating hours meet the criteria of low enough greenhouse gas emissions. A fluctuating electrolysis therefore would require immense capacities for electrolysis and hydrogen storage which cannot be implemented in practice due to economic reasons and required space. Moreover, hydrogen storage would lead to additional environmental impacts, not covered by this

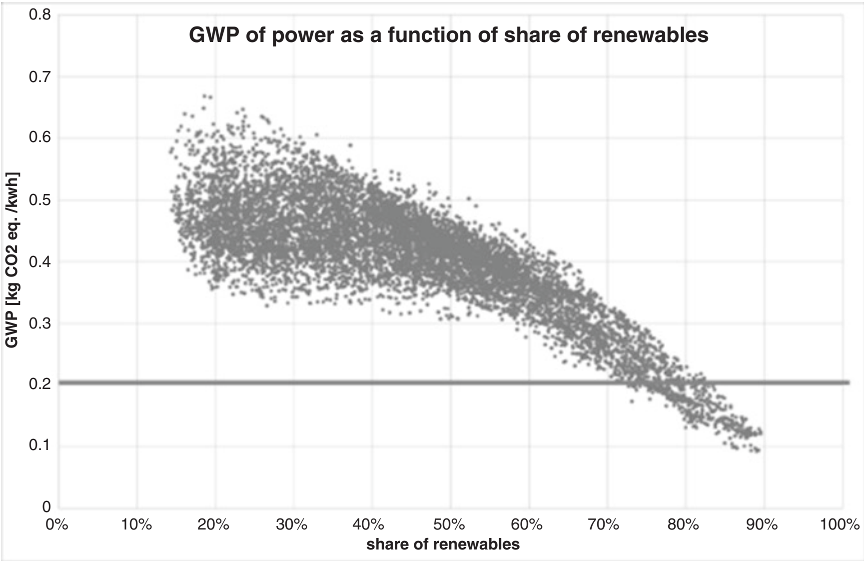


Fig. 4 Share of renewables at 200 g CO_2 eq./kWh

analysis. Hydrogen electrolysis during hours not meeting the low greenhouse gas level would cause a net increase of global warming impact of the CCU concept in comparison with the conventional processes of steel and methanol synthesis. This analysis is very sensitive to the assumed share of renewables and thus curtailment. Political targets for renewables have just been raised after the analysis. The potential of using excess energy for electrolysis will be recalculated under the new framework. The remaining hydrogen demand should be covered by hydrogen directly produced from renewable energy sources.

6 City Air Management

The City Air Management is an online web service which helps cities to manage local air quality at roadside measurement stations for the next 5 days (Fig. 5). It provides three basic functionalities for the air pollutants PM10, PM2.5 and NO_2:

- Monitoring the air quality at public measurement stations on a dashboard.
- Forecasting of air pollutants at these locations for 5 days.
- Intervention simulation and calculating pollution reduction of measures.

Instead of taking year-round measures, cities can take action when and where they have the highest impact.

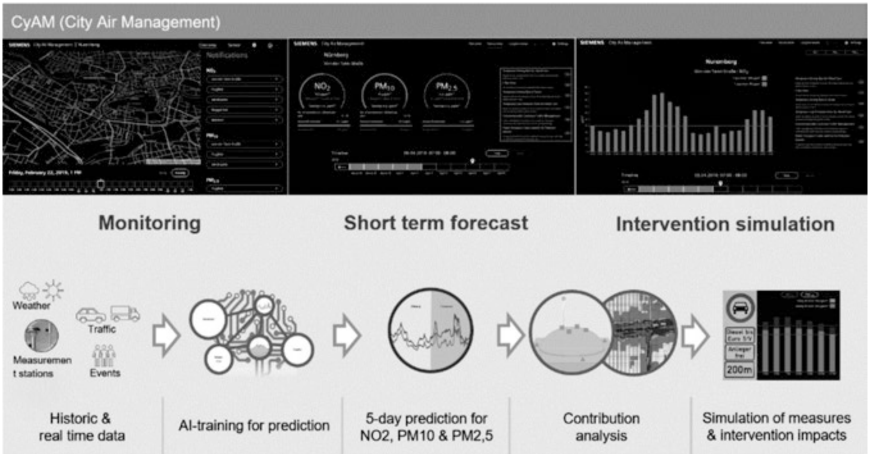


Fig. 5 City air management visualization and process

6.1 Methodology

Monitoring

Cities/counties/states operate their own air pollution sensor networks in order to prove their compliance with national or international regulation. This data is gathered on central servers and publicly available in most parts of the world. The CyAM has an API which allows this data to be pulled from this server or pushed to the CyAM as soon as the data is available. This is commonly every hour. The data for the individual measurement stations is visualized, categorized and benchmarked against the legal thresholds in a dashboard. It provides an immediate evaluation of the current situation and information on whether it is necessary to act. The latest history is also available for review, as well as the gliding annual average.

Forecasting

There are two common options to do forecasting for air pollutants, domain models and artificial intelligence. Domain models in this case are models which understand the physical and chemical processes of emission source behaviour and the atmospheric processes during transmission of pollutants. There are a vast variety of emission sources in and around a city. It involves tremendous efforts to assess all relevant fractions in real time. The modelling of the transmission (distribution plus the physical and chemical processes of the pollutants in the air) is time consuming, requires high computing capacities and is very sensitive to poor weather forecasts.

Thus, CyAM uses artificial intelligence to forecast air pollution concentrations at individual air quality measurement stations. It takes few available parameters which are available as forecasts. With historic data, it builds a temporal algorithm based on standard error backpropagation [2]. CyAM also uses air pollution measurement data, weather data/weather forecast data, calendric data and special events. The AI finds correlations and patterns in this data to predict air pollution for individual measurement stations. It doesn't contain any knowledge about the physical and chemical processes, responsible for these concentrations. Based on real-time data and forecasts of weather – and calendric/event data – a 5-day forecast is provided. The Advantage is a model which has high precision, takes little computing power during operation and requires few data points.

Intervention Impact Calculation
In order to calculate impacts of individual measures, a domain model is inevitable. But it only models the emissions which can actually be impacted by interventions, in this case traffic related. The traffic emissions are calculated for each hour of the following 5 days based on assumptions from historic data, calendric information and temperature forecasts for the baseline. Emissions for scenarios are then calculated for each intervention in SimaPro. Tailpipe emissions are based on HBEFA [3]. Some example interventions for specific street sections are:

- Allocation of eBuses on the lines passing the street section.
- Temporary driving ban of trucks or diesel cars for the street section.
- Low emission zones for the street section.
- Public transport ticket for air pollution season.

The local traffic-related share of the forecasted concentrations at the hotspot measurement station is determined correlating the forecasts of individual measurement stations in different locations. The combination of the traffic emission scenarios, the emission forecast and the traffic-related contribution of the forecasted concentration enables the prediction of the interventions' impact (Fig. 5).

6.2 Results

The accuracy of the forecast is measured by identifying how many of the 30% most polluted days were accurately predicted 5 days ahead of time. For NO_2 at the most polluted measurement station in Nuremberg, which is the lead indicator and location, this is 80%. Since it is an operational web service, the results are visualized on a dashboard as to be seen in the top three screenshots of Fig. 5. To evaluate the efficiency of the traffic interventions, the very same methodology is used as an ex post evaluation during the consulting phase of the project when the city selects which interventions they would like to have on the dashboard. The efficiency increase of temporary vs. all year-round measures is visualized in Fig. 6. The graph shows the results of the flexible truck ban for an individual road section in Nuremberg as a sum curve. The impact of the intervention is calculated for every day, relative to the annual saving. The jagged line is the historical sum curve from January 1 (on the very left, day 1) to December 31 (on the very right, day 365); see x-axis for the number of days per year. The smooth line sums up these savings, starting with the most efficient day of the year (on the very left, day 1), no matter if it is in January

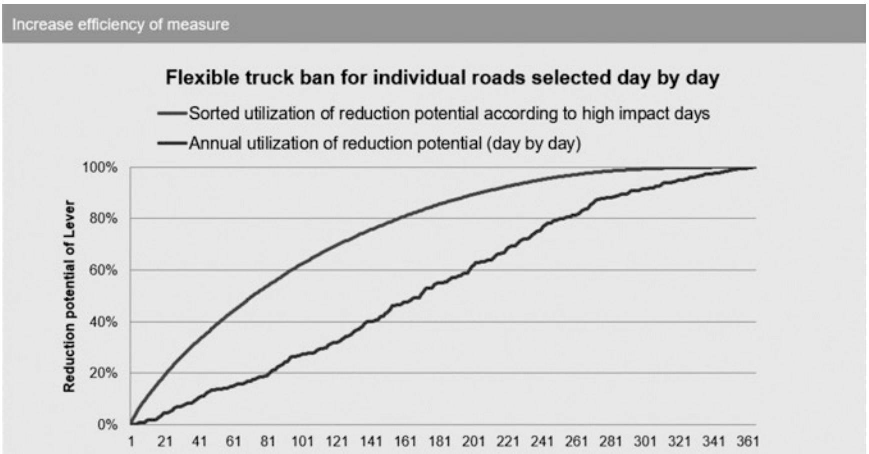


Fig. 6 Example efficiency of temporary vs. all year-round measures

or December, ending with the least efficient day of the year (on the very right, day 365).

6.3 Interpretation

The spread between these two lines shows the potential efficiency increase by implementing an intervention on a temporary basis, compared to an all year-round implementation. If a street section driving ban for trucks was implemented on the 70 most efficient days of the year, the yield in air pollution savings at the measurement station would be 50% of an all year-round implementation. In return, the least efficient 200 days, where there is enough wind to reduce emissions, only yield 20%. The efficiency of interventions measured as local air quality increase over days with traffic restrictions is most significant the fewer days they are triggered. Due to the fact that the forecast is not 100% accurate, the efficiency of the operational system is slightly lower, but cannot be determined at this stage of the project. Despite the efficiency, few cities apply such methods until now [4].

7 Conclusion

The use of environmental target functions in control systems has large potentials, reducing both global and local environmental impacts. Even when compared to economically optimized control strategies, environmental target function-based optimization can deliver significantly better environmental results. This is true even if cost of GHG emissions is priced in to some degree already at the energy markets, for example. The potential depends on the flexibility that is controlled and the volatility of the environmental impact. For some systems, environmental optimization-based control systems become absolutely crucial to create net environmental benefits compared to fossil-based processes. A large-scale hydrogen electrolysis for methanol production from CO_2 requires an optimization based on short-term prognosis for global warming impact of power production in order to meet the target of net reduction of greenhouse gas emissions.

From a methodological point of view, conventional LCA software and tools can deliver the environmental cost or burden of any state of the system for control purposes. The temporal and spatial resolution has to reflect the resolution at which any control system or short-term advisory tool operates.

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