SINTEF

Artificial Intelligence is paving the way for environmentally friendly mobility and logistics

Signe Riemer-Sørensen, Alexander Johannes Stasik, Anne Marthine Rustad, Dag Kjenstad, Petter Arnesen and Milan De Cauwer

Technology for a better society

Artificial Intelligence crucial to achieve environmentally friendly mobility and logistics

The logistics and mobility sectors are responsible for the majority of Norway's CO_2 emissions. However, it is challenging to meet the urgent need for significant reductions in these sectors due to many and complex relations. Data driven machine learning methods may be crucial in this hunt for large-reductions initiatives.

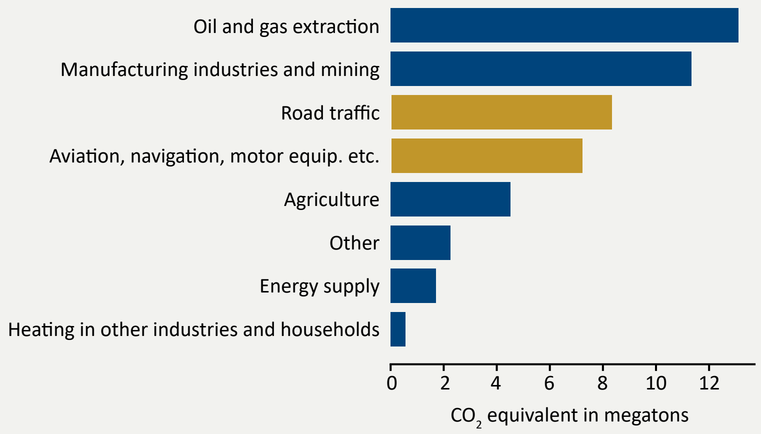
Climate change and reduction in biological diversity are global challenges for the 21st century. A significant contribution to climate-change related greenhouse gas emissions origins from our society's demand for transport and logistics, which is also a sector with large potential for increased efficiency and CO_2 reductions[1].

The future could be very different based on recent technological development: Imagine a swarm of connected autonomous vehicles that can transport Aunt Sophie to the grocery store along with a box of used batteries for the recycling centre, while bringing back the neighbour's online order for a used television, new goods for the pharmacy and piping for the local roadwork. The vehicles only drive when a service is needed and idling, and empty driving are minimised while the system guarantees timely deliveries. The swarm navigation system is aware of CO_2 emissions and will route the individual vehicles to collectively minimise emission. Guided by sensor generated data, the service is planned and performed on a 'just-in-time' basis ensuring minimal maintenance waste.

It may sound futuristic but artificial intelligence (AI) and its sub-branch of machine learning (ML) offer new ways to deal with complex systems and interpretation of large data sets, both of which are crucial for potential solutions to climate and environmental challenges[2]. In this whitepaper we consider mobility and logistics in the broadest context, highlighting promising applications of AI in the public and private sector.

Traditional applications of machine learning in climate research include sophisticated data driven climate models[3], analysis of large data sets, image analysis[4], and analysis of data from remote sensing devices[5]. This is extremely valuable for predicting and estimating the effect of our actions today and provide politicians with scientifically sound information in order to stake out strategies and political actions[6]. However, it also puts us in an observer position. To solve the environmental challenges and reach the strategic goals, society and industry need to be active players making decisions under both climate and economical constraints. Therefore, in this whitepaper we show how machine learning can be used as an enabling technology for reaching these goals.

CO_2 EMISSIONS BY SECTOR



Source: Statistics Norway

PHOTO: SHUTTERSTOCK

AI to support day-to-day climate actions

Reduction of climate and environmental impact may be achieved in several ways:

The first one focuses on the resources or raw materials used in a given process, for example fuel for trucks. To reduce CO_2 emissions, you need to consider changing the raw material composition, for example to bio friendly materials, or cleaning residue after the process, for example by additional filters.

The second way considers improving the overall efficiency to waste less resources across all types and time. Efficiency improvement also has a direct economic benefit through reduced use of resources in addition to an indirect economic benefit through regulations, for example via prices for CO_2 emission certificates.

The exploitation of AI in the process of making products and services more environmentally friendly and economically feasible can be split in two complementary approaches: Firstly, AI can be used to identify areas of potential improvement, and secondly, AI systems can be implemented for direct improvement of efficiency.

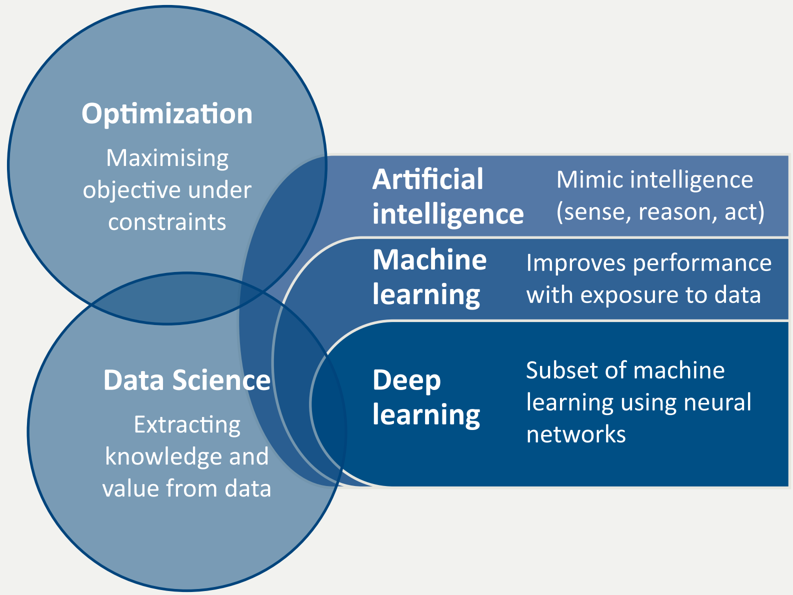


Figure 1 Data science is the concept of extracting knowledge from data in order to do data-based modelling rather than models based on pre-conceptions of the system. Optimization is the art of maximising an objective under some given constraints. Both data science and optimization are partly overlapping with artificial intelligence which is a broad description of algorithms that mimic intelligence in any possible way including sensing, reasoning, or acting. Machine learning is the subset of artificial intelligence dealing with models that improve their performance with exposure to data. Deep learning is a subset of machine learning that in which multilayer neural networks learn complex relationships in the data.

TYPES OF MACHINE LEARNING

Machine learning (ML) is a type of artificial intelligence (AI) and can be divided into three different branches, depending on the goal and the available data:

- Supervised learning can be used when the input and the corresponding label is known. Examples are image classification or time series prediction. Supervised machine learning can produce impressive results, but strongly depends on the quality and amount of the labelled data.

- Unsupervised learning tries to find hidden structure in data where the actual structure is unknown, also sometimes referred to as data mining. Performance of unsupervised machine learning is harder to estimate than that of supervised learning since the true value is not known. It can for example be used to find anomalies in data, allowing to predict and prevent failure of a system.

- Reinforcement learning is a flavour of machine learning where the algorithm interacts with an environment (in most cases via sensors) and receives a reward, depending on its action. This could be either playing a game or controlling a process in a factory where the reward is either points for winning or productivity of the factory. Reinforcement learning can be thought of as in between supervised and unsupervised ML since the reward for actions is known, but not the best actions. Reinforcement learning can find new strategies, but this often requires good models or large data sets to be trained.

PHOTO: SHUTTERSTOCK

Identification of potential emission reductions using analytics and AI

Machine learning and data analytics can be used as tools to identify areas with strong environmental impact and large potential for improvement in terms of more optimal usage of available resources.

By modelling processes using data driven methods, you can track the influence of individual impact factors and identify low hanging fruits. This allows for the largest improvement with the smallest investment, and thereby support the decision makers.

In this context, the advantage of machine learning is the ability to model complex relations, where an analytic model would require specifications of all relationships and hence it would need some of the information we seek to derive.

Example: Condition specific estimation of tank-to-wheel fuel consumption efficiency[7] is an example of a data driven analysis that enables deeper understanding of fuel consumption from petrol, diesel, and electric vehicles.

Tank-to-wheel efficiency functions can be combined with known relations between emission and a range of variables such as actual load, road conditions, and vehicle parameters, for example front area, to obtain situation specific modelling. This provides decision support to assess the impact of the driving conditions on the fuel consumption and the option of avoiding unfavourable conditions.

Indirectly, the functions also provide an estimate of total CO_2 emissions, which again informs of subsequent CO_2 fees and also contributes to improved life cycle analysis of the machinery and the actual cost of running it. Hence, there is not only an environmental motivation of reducing CO_2 but also an economical benefit.

RESEARCH PROJECTS

PHOTO: SKANSKA

PHOTO: SHUTTERSTOCK

Reducing idle time in road construction

In Norway, construction machines are idling almost half of their working hours. In addition, they are responsible for one fifth of the greenhouse gasses from the building and construction industry. Instead, imagine a civil road construction project where each machine always knows where the others are, what they are doing and what is the optimal way to organize the work.

To realize this, Skanska, SINTEF, Ditio and Volvo are collaborating on developing an artificial intelligence that can dynamically map the construction site and activity, identify sub-optimal working patterns, recognize effective routing and driving style, find out which machines are needed where, and can coordinate all machinery[13].

The goal is less emissions, shorter construction times and reduced costs. The digital tool under development will be launched commercially helping the whole industry to reach their sustainability targets. The activity mapping concept could potentially be repurposed for improving maps to guide last-mile deliveries.

Communication coverage along the road network

Cars are getting smarter and smarter with decision support based on data driven methods and machine learning. However, some of these smart functionalities require communication with central systems or nearby cars. For this purpose, spotty telecommunication along the major roads may become a safety issue.

The Norwegian Public Roads Administration, Norwegian Communications Authority, SINTEF and industry partners have worked to establish a calculation and planning tool for electronic communication coverage along the road network[16].

The aim is to cover both mobile connectivity and dedicated short range communication to ensure predictability in terms of connectivity for future information technology services and cooperative connected and automated mobility[17]. The tool is based on realistic signal path loss models calculated from current mobile network coverage mapped by driving on the road network. This is combined with knowledge of base station placements

Optimizing processes using AI

Artificial intelligence is not restricted to only identifying optimization potential, but also to realize it. AI allows to optimize critical processes in terms of time, required resources and environmental impact. Applications range very broadly from small-scale automatization of repetitive tasks, over scheduling of vehicle fleets, up to full scale optimization of airport traffic control as in the SINTEF-led SESAR VLD3 project[8]. The project developed and validated a system that enables tower and approach controllers to optimize mixed arrival and departure runway operations while ensuring safe operations.

Classical optimization methods require a complete description of the system and constraints to be imposed on it. That can be difficult to obtain from unknown or complex systems with sparse data, but data driven machine learning methods can in many cases alleviate the problem and the combined methods provide powerful solutions[9].

In many cases, usecase specific solutions can be built based on existing methodology like for example graph neural networks for non-Euclidian data or recurrent models for time series. Machine learning can also be combined with classical control theory, substituting parts of a classical controller[9].

In some cases, it is possible to bypass the classical optimization entirely or partly and instead use reinforcement learning or machine learning enhanced optimization. In the case of reinforcement learning an agent is trained to a desired behaviour in a system based on rewards, but without explicit instructions[10], [11]. In the case of machine learning enhanced optimization, deep learning is implemented to speed up the optimization process enabling solution of more complex problems[12].

Example: In warehouses, shipping pallets are packed with goods for further distribution based on orders and demand. Since typical shipping is limited by volume and not by weight, a high-volume filling factor directly translates into an increase in efficiency and consequently reduction of fuel consumption. When stacking differently shaped boxes on shipping pallets humans archive a volume filling factor of typically 85 per cent. A simple optimization algorithm can achieve similar performance, but when combined with an autonomous stacking robot, the problem complexity increases significantly and the performance drops to around 70 per cent. However, the drop can be re-claimed by combining the optimization algorithm with machine learning to speed up the search for optimal solutions.

RESEARCH PROJECTS

PHOTO: SKANSKA

PHOTO: SHUTTERSTOCK

Last-mile deliveries

E-commerce has been experiencing rapid growth over the last decade enabled by the maturation of multiple technologies. The consequence is an increasing number of last-mile deliveries from distribution warehouses to consumer's door-steps potentially putting a heavy strain on the local traffic network as well as the environment.

The massive increase in last-mile deliveries adds an extra level to the already complex challenge of optimizing the logistics. For last-mile deliveries, the optimization problem is often incompletely or incorrectly described, which is a challenge for traditional optimization techniques. Distribution Innovation and SINTEF are researching how this challenge can be alleviated with machine learning. As an example, poorly drawn or infrequently updated knowledge about the local usable network for distribution (roads and pathways) will lead the optimization algorithms to suggest suboptimal routing decisions. It has been proposed to apply machine learning to identify such missing information by merging information from different map providers, inferring information from public GPS traces or analysing satellite imagery. Using these AI centric methods to produce a more accurate representation of the world should enable more efficient routing.

In addition, last-mile deliveries can be handled by a wide range of transportation means such as pedestrian, bikes, small cars, and larger vans. While this adds to the complexity of finding efficient delivery routes, machine learning has the potential to assist well established optimization methods by learning relationships between transportation modalities and solution quality.

In a broader context, accurate world representations and complex route guiding provided by data driven machine learning algorithms will also be crucial for any kind of autonomous solutions whether being delivery services, ships, or drones.

The digital mountain crossing

Norwegian mountain crossings are heavily affected by extreme weather conditions in particular during the winter season. Some crossings report 30-50 periods with closed roads or convoys during a single winter season. This affects both private, public, and commercial traffic, and pose a problem for time critical logistics operations. For instance, transport of salmon is very time critical, and large values are lost due to unexpected delays. Hence, predictability is of utmost importance.

The Norwegian Public Roads Administration (NPRA) and SINTEF are collaborating on the development of AI based decision tools to predict local driving conditions to enable better route planning and thereby minimise delay-induced waste. The deep learning-based tools currently under beta-testing[14] are utilizing data from online weather roadside installations, inductive loops for traffic counting, speed measurements, and public weather forecasts[15].

Disruptive technologies and future challenges

New technological and social developments will change the requirements for future logistics and may have disruptive effects on the markets and significantly change the outer boundaries of existing services: The 20th century has been an example of centralization in terms of production. In the 21st century, however, there is an increasing demand for local products of food and energy as well as new technologies like 3D printing, allowing for local manufacturing. This will challenge logistics to transition and demand additional flexibility.

The boundaries between human mobility, goods and consumer mail and packages are predicted to become even more blurred in the future. The problem of co-coordinating different sorts of deliveries is so complex, that now it is almost unimaginable to have a single algorithm taking care of everything with current technology. But the ongoing development of machine learning enhanced optimization algorithms and hardware development may alleviate the challenge. A more recent example is the way virtual meetings have currently been replacing physical meetings and significantly reduced the demand for travel.

Classical analytics and subsequent optimization rely on historical data. This poses a problem when you want to use a model based on historical data to predict what will happen in the future. Machine learning algorithms are dependent on the data used for training. If continuously exposed to new data, either directly or via transfer learning, they become self-updating and will to a certain degree adapt to changes in the market. This presents an advantage over classical methods which are not easily adapting to changing conditions. For the logistics and mobility sectors these machine learning methods may be crucial to find more efficient solutions and large-reductions initiatives.

There have been impressive results from the machine learning in recent years in selected domains, like super-human performance in image recognition or AlphaGo beating the world's best human Go player. However, at this stage there are still no off-the-shelf solutions for all challenges.

Viable solutions for both modelling and optimizing systems with machine learning require significant amount of adaptation and fine tuning in close collaboration between data scientists and domain experts, mainly due to different systems, available data, but ultimately driven by individual customer needs. A major benefit from individual solutions is that the solution is lightweight and minimal, often allowing real time applications. Another advantage of minimal AI systems is that they can be interpreted through explainable AI (XAI), which is turning the AI mode from a black box into an explainable system. This is a general requirement when it comes to safety critical applications as well as to generate trust of users in the system.

Artificial intelligence also generates CO_2

Training large neural networks also consumes large amounts of energy. For example, the training of a single big language model is equivalent to approximately 300,000 kg of CO_2 emissions[18], corresponding to a standard delivery truck driving around the Earth at Equator more than ten times.

However, while the problem complexity of logistics is large, the challenges are computationally heavy rather than data heavy and, in many cases, improvements can be achieved with much smaller models trained on regular desktops or even laptops, leading to positive sustainability effects[19].

In summary, the mobility and logistics sectors have large emissions and a large potential for reductions, but it hinges on the ability to model complex relationships. Data driven methods and machine learning are already paving the way in some fields and will without doubt be crucial to provide such models enabling large-reductions initiatives in these sectors in the near future.

REFERENCES

[1] «Emissions to air,» SSB. https://www.ssb.no/en/natur-og-miljo/forurensning-og-klima/statistikk/utslipp-til-luft (accessed Dec. 10, 2021).

[2] S. Rasp, M. S. Pritchard, and P. Gentine, «Deep learning to represent subgrid processes in climate models,» PNAS, vol. 115, no. 39, pp. 9684–9689, Sep. 2018, doi: 10.1073/pnas.1810286115.

[3] T. R. Andersson et al., «Seasonal Arctic sea ice forecasting with probabilistic deep learning,» Nat Commun, vol. 12, no. 1, p. 5124, Aug. 2021, doi: 10.1038/s41467-021-25257-4.

[4] E. Rolf et al., «A generalizable and accessible approach to machine learning with global satellite imagery,» Nat Commun, vol. 12, no. 1, p. 4392, Jul. 2021, doi: 10.1038/s41467-021-24638-z.

[5] N. Kussul, M. Lavreniuk, S. Skakun, and A. Shelestov, «Deep Learning Classification of Land Cover and Crop Types Using Remote Sensing Data,» IEEE Geoscience and Remote Sensing Letters, vol. 14, no. 5, pp. 778–782, May 2017, doi: 10.1109/LGRS.2017.2681128.

[6] «Om sjette hovedrapport fra FNs klimapanel (2021-2022) - Miljødirektoratet,» Miljødirektoratet/Norwegian Environment Agency. https://www.miljodirektoratet.no/ansvarsomrader/klima/fns-klimapanel-ipcc/dette-sier-fns-klimapanel/sjette-hovedrapport/ (accessed Jan. 13, 2022).

[7] O. A. Hjelkrem, P. Arnesen, T. Aarseth Bø, and R. S. Sondell, «Estimation of tank-to-wheel efficiency functions based on type approval data,» Applied Energy, vol. 276, p. 115463, Oct. 2020, doi: 10.1016/j.apenergy.2020.115463.

[8] «Enhanced RWY Throughput (SESAR PJ 02 EARTH),» SINTEF. https://www.sintef.com/en/projects/2016/sesar-pj-02-earth-enhanced-rwy-throughput/ (accessed Dec. 10, 2021).

[9] M. P. Deisenroth and C. E. Rasmussen, «PILCO: a model-based and data-efficient approach to policy search,» in Proceedings of the 28th International Conference on International Conference on Machine Learning, Madison, WI, USA, Jun. 2011, pp. 465–472.

[10] W. Kool, H. van Hoof, and M. Welling, «Attention, Learn to Solve Routing Problems!,» arXiv:1803.08475 [cs, stat], Feb. 2019, Accessed: Dec. 10, 2021. [Online]. Available: http://arxiv.org/abs/1803.08475

[11] R. S. Sutton and A. G. Barto, «Reinforcement Learning: An Introduction,» p. 352.

[12] V. Nair et al., «Solving Mixed Integer Programs Using Neural Networks,» arXiv:2012.13349 [cs, math], Jul. 2021, Accessed: Dec. 10, 2021. [Online]. Available: http://arxiv.org/abs/2012.13349

[13] «Datadrevet anleggsplass,» SINTEF. https://www.sintef.no/prosjekter/2020/datadrevet-anleggsplass/ (accessed Jan. 13, 2022).

[14] «Fjelloverganger.» http://mobilitet.sintef.no/fjelloverganger/ (accessed Jan. 13, 2022).

[15] «Den digitale fjellovergang,» SINTEF. https://www.sintef.no/prosjekter/2020/den-digitale-fjellovergang/ (accessed Jan. 13, 2022).

[16] «Lambda Tool Prototype.» https://mobilitet.sintef.no/lambda/ (accessed Jan. 13, 2022).

[17] H. Seter and P. Arnesen, «Innlegg: Glem ikke fremtidsbilene når 4G-hullene langs landeveien skal tettes,» www.dn.no, Jul. 08, 2021. https://www.dn.no/innlegg/teknologi/bil/telekom/innlegg-glem-ikke-fremtidsbilene-nar-4g-hullene-langs-landeveien-skal-tettes/2-1-1036625 (accessed Jan. 13, 2022).

[18] P. Dhar, «The carbon impact of artificial intelligence,» Nature Machine Intelligence, vol. 2, no. 8, pp. 423–425, Aug. 2020, doi: 10.1038/s42256-020-0219-9.

[19] R. Vinuesa et al., «The role of artificial intelligence in achieving the Sustainable Development Goals,» Nat Commun, vol. 11, no. 1, p. 233, Jan. 2020, doi: 10.1038/s41467-019-14108-y.

Contact us

Signe Riemer-Sørensen
Research Scientist
signe.riemer-sorensen@sintef.no
+47 411 84 810

Alexander Johannes Stasik
Research Scientist
alexander.stasik@sintef.no
+47 988 36 348

SINTEF

www.sintef.no

Technology for a better society