Power of Unified Manufacturing: **Revolutionizing manufacturing with machine learning**

Webinar Transcript

Section 1: Introduction

William: I think with that, I'm happy to introduce CGI's Marcel Mourits moderator for today's panel. Marcel, over to you.

Marcel: Thank you, William. And yes, I'm looking forward to our conversation on AI, machine learning in manufacturing. There's a lot of opportunities out there. There's also a lot of untapped opportunities out there, and it's in that area that we will be discussing with Alexander Daehne, an AI Manufacturing Lead at SAS and Nathan Eskue, Professor of Artificial Intelligence from Delft University. My name is Marcel Mourits. I'm DC Expert at our Manufacturing Center of Excellence. And I would like before we kick off the conversation, that each analyst introduces himself in several minutes. So, may I give the floor first to you, Alexander?

Alexander: Okay. Thank you, Marcel. So, I'm Alex Daehne. I'm with SAS now for 20 years. You probably see my inventory number already there. And for the people who don't know SAS Institute, SAS is doing nothing else but analytics for more than 40 years. When it comes to advanced analytics, SAS is the quite leader in this space regarding market share so we have a lot of experience. Since I started with SAS, in the beginning—I told that to Nathan (we chat just before)—was to evangelize the manufacturers about the use of analytics, AI, machine learning and things like that.

And let's say, over the last couple of years, it has been a strong momentum that now, customers come with specific requests, "Hey, can analytics, can AI, can machine learning help me with this problem?" And I've been working with a lot of companies around the world—with Shell, with several steel companies, with Volvo Trucks, with Lockheed Martin. So, all kinds of sectors in manufacturing and there's a big difference regarding data availability and possibilities.

So regardless, AI is, for me with all the experience, it's not, let's say, the crystal ball. There's a good quote, "It's all about modeling. All models are wrong, but some of them can be very helpful." And if we find these use cases where the models are very helpful for the business, this is the right business opportunity. And with this, I'm handing over back to you, Marcel.

Marcel: Yeah. Thank you, Alexander. I really like what you said about models, and that's true. All models are wrong, but it's funny, I haven't heard it in a long time. But it's really, you know the whole idea about digital twin, where there's a cloud of ideas about it, like that's the exact replication of what goes on in real life. No, it isn't. It's just another model. There's just some more advanced technologies perhaps in there. And it's a new world. And if you apply it right, there's actually nice new functionalities in there that you can use.

Alexander: Right.

Marcel: Over to you, Nathan. Your introduction.

Nathan: Thank you. Yes, I'm Nathan Eskue, Associate Professor of AI in Manufacturing at TU Delft. My journey has been all over the place. I worked for about 20 years in the United States with various aerospace firms, starting with NASA and then working at Raytheon Technologies, Orbital and then, Northrop Grumman. A lot of my work has been in the launch vehicle and satellite area, and from business to finance to project management, and then getting more into supply chain and some of the analytics behind that. And really, during that time, taking process improvement focus on my work and really framing the world around me as problems and problems to solve, instead of what tools can we use to make things better? It's what problems can be solved, and then what tools are there that can best solve them?

And from there, it led to deeper and deeper analytics. And then finally, into the world of machine learning, AI, simulation and I became an AI architect for the manufacturing area of Grumman, looking for those different problems, also looking for innovations and then, seeing what sort of different problems can we apply and solve for that? I ran into some deep questions that I really wanted to focus on and research on, but it wasn't really, there wasn't money in it from an industry standpoint. So, I got the opportunity to go over to academia so I could jump into those topics more, which is what I'm doing now and really enjoying that.

And a lot of my journey has been looking at the digital thread, looking at what additional benefits we can have, when we start connecting that data in each step of the process and looking at what problems we can solve using AI, using machine learning or using a whiteboard and a marker if that's the best solution for that. So, a lot of my research inevitably involves AI, but it also brings in VR, AR, even blockchain and even a little bit in the quantum realm, just depending on the problem we're going to solve.

Section 2: Understanding the value of artificial intelligence

Marcel: Okay. Yeah. Thank you, Nathan. I see. Okay. That's good. So, there's a lot of, you know, high expectations, maybe even overblown expectations, still in the world about artificial intelligence, about machine learning. Like, you know, you can apply it for everything. It solves everything. It automatically improves your quality, predicts when your machines break down, predicts sickness of personnel, whatever. It's going to predict and solve and optimize everything. Now obviously, it doesn't fulfill on that promise.

But what are applications where you say, "Hey, that is actually something." And I'm going first to you, Nathan. What are areas in production that you have seen or that you're witnessing right now where you say, "That's actually where AI is really valuable." That's where it's mature enough to say, "Put that on your short list, if you want to start, if you're ready for working with AI, start there."

Nathan: Right. No, that's a great question. I think AI, like you said, there's that big promise. And in some ways, that's true. What isn't said is that an organization needs to be prepared for that. And in large part, that amounts to, do you have the right data and do you have enough control of the process to be able to make use of that data? And so, I find, even things that could offer a lot of benefit, the organization isn't ready for. Where it often is ready for are those areas where they're already collecting a large amount of data or have the ability to collect data on a large number of items. And where I see a lot of immediate benefits is using object detection and classification, either with photos or even with some types of data for the sake of quality control, for the sake of sorting and even looking at other types of data, whether it be financial data or signals, where there can be some type of regression, where it can give a good estimate of what it thinks will happen next.

And so, from those problems' standpoint, can I separate something? Can I identify what this thing is? Can I identify if there's an anomaly and can I predict what's going to happen next when there's enough data there? I think that we have a lot of really high-quality algorithms that can be more easily employed.

Marcel: Okay, that's interesting. You mentioned two things there. One is a really great solution option and the other one is the availability of data. I guess we will be addressing that later on when we are discussing, “Why aren't we moving or as fast as we would like to move?”

Nathan: Right.

Marcel: But first, I would like to go to you, Alexander, to see if, you know, do you see the same or do you see also other areas where you think, “Hey, I would like to point out something else where there are some…I wouldn't call it low-hanging fruit, but definitely the maturity in algorithms and in applications that you take the really innovative aspect off of it and you can just choose to go and apply it in that area.”

Alexander: Yeah. So, there are I would say, it just amplifies also the story that Nathan told earlier, that I think two wide areas of use cases of AI, machine learning or analytics in general in the manufacturing space—The one that we all love is, “Hey, this wonderful thing. Hey, we solved the big problem that saved millions a year and whatever.” And of course, they are great. But in no company there are, or in each company there are probably five (maximum) of these use cases that make big, big difference where what's often forgotten is the wide basis. It's just kind of basic anomaly detection. I've been focusing a lot on process manufacturers over the last couple of years, and they drown in data from their automation system, and they can't monitor each and every little tech that's generating data in seconds, milliseconds, whatever. And some of them are not important.

We have an example of one of our customers in Sweden, Swedish Steel. In the steel production, they have the descaler, where they remove the iron oxide from the hot slabs before it goes into the loading process. And it's a high-pressure pump performed with bar and another six pumps underneath it to feed that high-pressure bar. And this equipment of course is very, very reliable. So, it breaks down every two or three years or has an issue. Let’s say, it doesn't break down but has an issue.

Marcel: Yeah.

Alexander: Then let's say if there's an issue and that happened about two years ago or so, the production’s down, the whole production for quite a bit. So, would you set an operator there to monitor an equipment where nothing happens? No. So, it's just the case that's a typical use case for anomaly detection. “Oops, there is something wrong. Oops, have a look at it or have a close look at it.” And by investigating that later on, provide also the engineers, in this case, the maintenance engineers, with the right information to do a location of what that anomaly really means. Because the anomaly detection model, especially when you use AI models, they are not self-explanatory. You need to provide them with some meaningful information to make the right decision. Only then it makes sense. If not, “Oops, I knew something was happening. I can't do anything against it. It will happen anyway.” So, it was a nice exercise, but it didn't help anyone.

So, these are the two cases, the same with image recognition, that this is what AI can do. It can do it fast. It can do it very accurate and replace people. Is that a process that you should always fully automize? Probably not. Because at the end of the day, as I said earlier, it takes the right decision out of that information. And sometimes, this is what AI machines, computers in general, are not good at—following decisions if there are those strict business rules and if it's a little bit more complex, with rules it is easy. But if it's a little bit more complex, then you need the human judgment to make the right decision, and that is to have the right approach to it and the right user interface to support a good decision.

Section 3: Recognizing the complexity of AI in machine learning

Marcel: Yeah, I recognize that. Would that be something—maybe the subject comes back at the end if we have a bit of time, if we want to explore something like hybrid AI—where you mix in human decision-making and reach it like augmented reality? But then with AI-based information, where AI doesn't take the decision but just gives higher level, better information to make a decision.

Nathan: Right.

Marcel: And then, let me see something else that you said. So, anomaly detection. That reminds me of a case that we looked into not too long ago. Also, once every now and then, maybe every two months, a certain machine broke down. It just got clogged and then, you know, it wasn't broken. It just got clogged and didn't work anymore. It took an operator half an hour to clean it, and then it could run again for another two months. And they did a lot of effort in trying to predict that moment. And then, they realized that it would take quite an investment to actually predict that, which they will never earn back with the half-hour of production goals.

And so, it's those kind of things where you then better be, “Okay, put the threshold a little bit lower.” Just, if you can somehow indicate like there is a little bit of a deviation happening in the process, maybe you should go look at it. And that's much easier to find, a much lower investment. And sometimes you just have to accept, “Okay, sometimes we just need to blame that thing.” It's half an hour of work. It's a nuisance. Get over it. Focus on something else.

Nathan: Exactly.

Section 4: Overcoming business challenges in AI adoption

Marcel: If we say focusing on something else and I will continue with you, Alexander. You touched on we touched in our conversation already earlier. Like, you know, hurdles to actually start moving. Data was one of them. But there's other hurdles as well. Even if you have a lot of data in order to get something running, that's like an app or what is it that's maybe a question on its own already. What is running and where is it interfering with? Can you say something about what you’ve experienced in working with companies where they struggle in order to have our audience learn from that and you know, maybe prevent those hurdles?

Alexander: It is, you know, I could probably talk for half an hour only on the problem of data. I would skip that. I guess everybody is aware of that. Without availability of the right training data, a model can be only as good as the data is and that's the one thing. If you have enough data to develop, it’s to have a good business case behind it. The biggest hurdle is doing the next steps. Deploy that into your standard operating procedures.

First of all, getting the insights is in many cases, already, “Are we good enough for the engineer? Okay, now I have a much better process inside or whatever the problem behind it was, that really doing the next step in automizing that and take more stupid workload by just, “Okay, we’re pulling that into action.” If we take an automated decision, that is one thing. We can interact with the control systems whatsoever. That's from a technology point of view, not a problem at all.

In most cases, we see, what I would say, an augmented decisioning—which means we provide the operator, the shift manager, whoever is concerned, the maintenance manager, with all the information he needs to arrive at a conclusion and make the right decision. And that would be in real time. That would be on a daily basis, depending on the use case. That's another thing that right now, with the misconceptions of AI, everything needs to be real-time which is nonsense. I prefer talking about “right time” because let’s say, if you overflow people with information, you will not gain anything.

But the last step, it will take a lot of change management for a lot of companies [who] underestimate, to get all people on board. If we operate, the engineers don't trust what's happening there, what's calculated there. They will never use it. They will not change the way of working. And if they don't do all the work, it’s useless. So, you need to put a lot of focus. The best thing is, include them right from the start. Who are the end consumers? That they know at certain standard, “Okay, how did we get to these results?” And then the next thing, when do you need information? What information do you need to make the right decision or can we fully automate that? It should be their decision because they own the process. And that's quite often overseen. And at the end, everything data scientist did damage, “Oops! Now what [do we] we do with it?” And if you include them right from the start, it works much, much better, much, much smoother and also helps them. It's best practice from companies where we see that they are able to scale. We see little pilots, here and there all over the place. But if you scale, it's only when it's a culture of working together and collaborating with the end users.

Marcel: I really like what you're saying. That's quite a nugget of gold that applies everywhere but in particular, in AI, in machine learning, advanced analytics kind of applications. Apply to people who are going to use it, who are going to contribute to it, who are going to design it. Involve them from the start. Make them part of it. Let them co-drive the development. Otherwise, you get those situations that, you know, we sometimes see where a separate change management team has to come in to, you know, make them accept the solution. And nobody wants to be forced at a solution that, you know, you weren't part of.

Alexander: Absolutely.

Marcel: Yeah, I recognize that very much. Thanks for that. Basically, same question for you, Nathan. Are there more hurdles or Alex mentioned already all of them?

Nathan: Right. Well, at the risk of repeating, I can't stress enough how much I agree with what Alexander said. In my experience, I've seen when projects go wrong, it's when (no knock on data scientists or software engineers) but when a project is led by, from an IT focus, it usually fails, unless the biggest boss likes it. And then, they make it succeed from their perspective, which means the people who are doing it don't like it at all. Because as you said, it's forced upon them.

Where it's most successful is forcing yourself to not think about AI, not think about a neural network or these other fun names that we like to say, “Oh, wouldn't it be cool if we had this?” But instead, and I have a few different exercises I've learned. That when I'm working on a project, like you said, Alexander, I want to, what's called “walk the process”. I want to physically be there. I want to talk to Cathy in Accounting and say, “Okay, let me sit next to you. And if you're willing, I'll buy you a soda or something nice, and I will ask you dumb questions for half an hour while you do your job, because I want to see how you do your job. And then, that will inform us of what your process is, where you make those decisions.” And I think of it as actionable intelligence, you know, that I need to know the information at the right time.

But for me, it's, “What do I need to know to make the decisions to do my job?” And what I found is, that can help quite a bit. But at the same time, the people who are in the process, who live the process every day, by I think by human nature, they start to get surrounded by assumptions of what can and can't be done. And so, you have to break them out of those assumptions because that's where the real innovation happens. It’s using the people who live and own the process and pulling that creativity out of them, but forcing them to break through these barriers that they might not even realize are there.

And so I use, the term “omniscient”. So, if you could know anything, if you had this godlike power, if you could know anything in this situation, what would you like to know? And then, you get some very interesting metrics that you probably didn't expect. You might say, “Well, I wish I knew if this department over here was about to send me something” or “I wish I knew how many errors were going to be in this report so I could deal with that ahead of time.” And then I say, “If you could be an oracle, if you could predict the future, what would you want to know right now if there was no barriers, what would you want to know?”

And by asking those two questions and saying nothing is off the table, and pretend like, you know, you have this magical ability, a lot of times, more often than not, there's at least a path from where you are today to what they're asking for. Sometimes it's difficult because you might not have the data. Other times, it's ridiculously simple because they're asking for something that someone else already has, and they just have never talked because they're in another department or organization. And so, it comes down to that process flow of information. And to me, that also is one of the benefits of building up to an AI solution. If the process leads you there, is that, it's all about who needs to make what decision at what time?

So, for example, right now, we're focused heavily, my team, on process monitoring. We want to know, within a manufacturing process, anomaly detection is good, and it's really what we can do right now, but from a lower TRL or more scientific, we want to get this out there in five years. I want to know 100% of the variation in this process right now, and I want to know how that relates to the final outcome. And my omniscient oracle self says, “For this process, like we're doing ultrasonic welding of composites right now, I want to not care about anomaly detection because I want to know, as it's being made, what anomalies will be there at the end?” So that's what I want to know.

And then the next question becomes, and here's where we haven't answered yet, should that if we can get this process monitoring. That's fine. It's great to predict that there's a problem, but that doesn't really help unless you can prevent that problem. So that process control to make sure all of your barriers are in line, I want to know who needs to make that decision. Is that something we can automate and keep that in line? Or is that actionable intelligence that a responsible, experienced technician can take his input and then make an informed decision?

So those are the things I see as the biggest hurdles and some of the ways I found in kind of breaking through. And ironically, only a small percentage of that is AI. It's more about managing the process and the people, and letting that guide you wherever it goes and having to make an explicit agreement with your stakeholders that, “Listen guys, this might not involve AI at all. This might involve a simple Excel spreadsheet that you get once a month. But, if we all agree that we're trying to solve a problem and not install AI, then we can go on this journey together.”

Section 5: Instilling an AI culture within an organization

Marcel: Yeah. I really like that. I can relate to that a lot. One of the people in the audience they already asked a question in line with this is, how do you instill an AI culture inside the company? Any best practice, training, cross-skill assignments, anything? My first impression, and I'm going to go to you, Alexander. My first impression on the answer is, well, first of all, that the whole notion of AI culture seems to be a little bit contrary to what Nathan is advocating. Like, don't make it about AI. Make it about solving problems. And if AI comes around the corner as a potential solution, that's great. On the other hand, it does help if there is a culture around, you know, where the fear or the uncertainties around AI or the misconceptions around AI are taken away. So at least all those hurdles, those hurdles are gone. But any view or experience from your side, Alex?

Alexander: Well, I guess that's one of the toughest questions at all, and I’ve seen a lot of companies who really succeeded on this one. It's with a pure training approach, it will not fly. And let's be honest, not all people will be good data scientists, especially not trained engineers. And I'm talking about myself. I have no clue about AI. I'm just as stupid, and I accept that. I know what AI can do, but I don't need to understand how it works. That's one thing. So getting the people on board and getting some excitement are the two things that worked well.

We haven't done everything perfectly with our clients. But what really worked well when we start, it could be a department, could be the whole organization, but it's much better when you focus on, “Hey, that’s production. This is maintenance,” whatever department this is. We start with a workshop with possible end users, and process owners as Nathan said it. And we start up a workshop with other customer use cases to show them a little bit the art of the possible, just to open their minds. You can do this. You can do that. Because there might be some misconceptions and fear whatever, “Will that replace my job?” All these kinds of things go in there, and giving some real-world examples helped to bring down, to lower the border, and the concerns about that and helped people opening up. And then they should come up with possible use cases, and then we group them, categorize them, and then together we decide, they, the business users, they need to decide from a business value point of view. How would you rank those? What is the most important one for your company or your department? What's second? Whatever. So that's the side of the business case.

With our experience, we then do the feasibility check. Is enough data available? Or does it take half a year to get good training database in place in the first place? So, what we estimate on our side then is how long will it take to solve that problem? And then you can rank that and jointly decide, "Okay, we have this business value behind it. We are, could roughly solve that problem and put it into production in three, four or five months." And this is kind of a statement of work. And then first of all, because that's all assumption.

And then, we start on the next step. We work with offline data. Because you don't, before you haven't looked into the data, you don't know what's in it because you, also on this use case, you have success criteria. And if you want to improve whatever kind of KPI by x percent, you need to check that. So, we do a back test of historical data and see, is it working? Again, a very fast, slim process. I wouldn't call it "quick and dirty," but it's a little bit like that. So, it doesn't have to look great. It's just the results that we present based on historical data. With our approach, we will be able to improve this process by x percent. Is that good enough for you to deploy that in this tough last step when you need to interact with level zero, level one, level two data with the business systems where you need to change manage all these kinds of things? We want to do this tough step, which is the most costly and time-consuming only if it makes sense, if we are able to meet or exceed the expected results. And that's, and with this, you have had already a backlog of possible use cases. And if you implemented two or three or four in the company successfully, this creates a momentum on its own. And then you have won. If you achieve that, then you have won.

And then you don't need to think about trends that people will ask for, "Hey, I have a problem. Can you work on this?" It also provides the business users with some analytical capabilities, visualization capabilities of their data that they can play around. They have ideas, a couple of ideas each and every day. Let them test the hypothesis on their own. They don't need to model it. They don't need to develop neural networks. But if they understand the problem, they can do all the prep work before it "scares" good data scientists. And that also reduces the hurdles of scaling successfully.

Marcel: Yeah, yeah, absolutely. And in that way, you can create momentum. And I like the way you were talking about it in the sense of, you know, you don't talk about where shall we start, do a proof of concept, whether we try something. You talk about real problems that you intend to solve, and it's in that word "intent" where I tend to see differences.

And I'm curious, Nathan, maybe from your current experience or your previous experience in aerospace, like working in a real company, being like, do you see also the intent by which an analytics project is started impacting the chance of success? Like if you start with it like, well, let's see if AI maybe can solve this. And I know that's already countered the way you suggested to do it, but it still happens quite a lot versus "We just take a decision. We're going to solve this. And whatever it takes, it's just going to happen." We just don't need to design a solution. Any reflection from your experience on that?

Nathan: Certainly. Well, when it comes to a problem, and I say that we agree that AI might not be the solution. At the same time, if we're honest with ourselves, we know that, you know, in some cases, there's a chance, based on an initial look at the data, the process, this looks like a good candidate. So, we also are honest with ourselves that, "Yeah, we're thinking about that from the start," that, "Hey, AI could definitely solve this if everything's right," but still trying to remain pure to the following the problem to the solution, wherever that might be. I think that leaves more opportunities for if you have to make a turn or not.

I think one thing that helps in terms of, in terms of, that being able to accomplish that and meeting resistance, you know, people being afraid of that, I see two things. I see the fear of technology and then the fear of being replaced. And in terms of the fear of technology, AI, I ask the question sometimes, "What does AI mean to you?" to a group of people, and everyone has a different answer. And even I have a different answer over time on what I think AI is. And I don't get into debates with people on it because I don't know if I'm right or not, but I know that it's very fluid, and it's on this continuum that starts with data and then gets into analytics, and then at a certain point, it starts to become more machine learning and AI. I think the technical definition is when it's not explicit programming, when the code itself becomes less explicit. But in terms of that, when you look at an organization, I think the fear of technology is lessened when you say, “Hey, let's become a culture that cares about data, that cares about using data to make right decisions.” And then, as Alexander said, seeing those wins either from other companies or within your own organization, saying, “Oh, well, you use data, and it's helped inform you, and you got a better result,” or “You automated this process, and it made it more efficient.” I think if you take that approach, and if there’s some education in terms of what AI is and isn't, what it can and can't do. I think that helps in terms of the fear of being replaced.

I think you as a company have to decide, are we going to be the company who would care about automating for the sake of lowering our headcount? If you do, then just be honest about it so people can justify being afraid of being replaced. At least there's that openness. What I talk to people about is, assuming that the company believes this is, “Listen, our goal is to find somewhere in your process where we can automate it so that you don't have to do that anymore. But the reason we're doing that is your experience, your intuition is much more valuable than some of, if we can automate part or all of your job, that just means that we can unlock you and use you for something much more important than what you're doing now. Because if we can automate that, then I want to use your intuition, your expertise. I want to use it for something even more important that doesn't exist today because we haven't had the convenience of being able to do that. So that's why you need to be part of this process, and you need to hope that we can automate this so that you can actually do something that's even more in line with your capabilities.” And so, I think that helps with the fear of being replaced. Again, unless that's your goal is to replace people, and then that's a different story.

Alexander: Yeah.

Section 6: The future of AI in manufacturing

Marcel: Yeah. No, absolutely. I think two more areas looking at the time. One, we've seen some AI examples where you think, “Oh, these are quite mature already.” We've discussed some hurdles where we are like, “Hey, this is where companies run into, people run into, and these are ways to deal with it.”

I would like to see, like from a technology of AI perspective, and I will continue with you, Nathan, first. Currently, most of the AI models are made in an AI environment with an AI language, and it's very tailor-made. To what extent is that still the way we work five or ten years from now? Or is there going to be a development where you say, "Hey, it's probably going to be built into your ERP, into your manufacturing execution system, into your maintenance system. It'll just automatically start doing the predictive parts or whatever parts.” What do you think? Is that possible? Do you see that happen or what's your view?

Nathan: Wow. Okay, that's a really great question. And honestly, one that I don't think I've allowed myself to think that deeply on, simply because I feel probably pessimistic about that. Because I think, with is as hard, for example, on the process monitoring, our goal is to look at how to track process monitoring, and we're taking three different manufacturing processes right now, and each one of those will be its own journey. But assuming the best-case scenario, we have this massive success on all three, the end goal is to generalize that and say, “How much of that can we package up into…” as you said, “…a built-in starter package?” And then the real question is, what's the additional cost when we get the next process? What additional costs do we still have to put into, in terms of data, in terms of context, that will allow that to do what it needs to do?

Now, I do think that if you have control of the process, so like ERP, there are some standard things that are important. You want to look at different labor force, what sort of skill sets you have. You want to look at supply chain, your supply and demand, and all the probabilities that go into that. And then, you have your damage rates and your variability of how long it takes to build something. If you have a structure like that, that has a fairly stable architecture as ERP does, even if whether you're building little Lego sets or a launch vehicle, it's all the same thing. You're trying to make this end thing by using little parts that you get from a bunch of different people to make bigger parts and bigger parts, and then put it together. And then, there is some testing. So, it's all the same process. With something like that, I can see some built-in models that still require tuning and probably need some expertise in terms of tuning, but I can see that in the next five years. I don't see anything close to general AI saying, “Hey, throw some data at me or talk to me about a problem and I'll find some optimized solution for you.” If I'm wrong, that would be great, but I don't see it happening.

Marcel**:** I'd like to probably say that it’s totally different. No, I'm just joking. What's your view, Alexander?

Alexander: It's the same and the important thing that Nathan mentioned it. At the end of the day, you want to have an optimized next process. That should be the result. And we've been working a lot with customers on process optimization, mostly in the manufacturing space directly. But the complexity of these problems, this is where I see the hurdles. There are so many constraints, which are different for each and every process. From the outside, it looks almost the same, but the constraints are very, very different. And if you need to spend so much time on fine-tuning these constraints, that's I guess…maybe I'm wrong, maybe I'm too pessimistic on this one or too negative. But I see it for, kind of a simple process, where you have what we already see with customers.

We work, for example with Volvo, with half the trucks company. We have kind of…we support and validate the alarms that more than 400,000 trucks in North America generate on the road and take the decision, “Hey, is that a serious problem?” Or we all know that experience, “Oops, there’s a red light on my dashboard, and the next time it will never show up again.” So, to really validate, is that a serious issue? Then, we do that on different models, different makes for the Volvo Group. They have Mack trucks. They have Volvo trucks. And in this area, it works where you have a big training data and also a big... they use the same components, and they have the same failure modes and all these kinds of things where you have that comparability and little, not too much variability. There you can turn it into a core process optimization as such. I don't see, let's say, the crystal ball right now. We're working on it. But I think not within the next five years, if ever.

Section 7: Future applications of AI

Marcel**:** Yeah. Okay. Let me see. We are at the point where we promised to open up the floor to people asking questions. We had one question in the chat. We discussed that. We got a big thank you for that. Any other questions coming up either in the chat or if you open your microphone and just want to ask something if that's easier? Go ahead.

Well, it doesn't seem like many questions from there. That could also mean that they like the conversation so far. They’re still here. Everybody is in.

Alexander**:** Nathan and I are talking too much.

Marcel**:** Well, they probably like to hear it. So, at least I like it. Even though I'm in the field now for whatever quite some time, I really learn a lot. It's really inspiring to talk with people who have been there longer than I have and have lots of experience, too—depth of experience to share. Thanks, Alex.

So, one other question, maybe to round it off, and that is, looking forward again, is there any application of AI that you think, that will be great? We are not there yet. But maybe again, three to five years from now, we might see the first implementations of that somewhere in manufacturing. That would be awesome.

Nathan, you both know that. But Nathan, you go first.

Nathan**:** I've been excited about this one. For me, the holy grail that is very difficult, except in very specific situations and some people don't even think about this is AI, is genetic algorithms, where you simulate through millions of generations, starting with no intelligence whatsoever and mimicking evolution until you get something unique. And I think it's exciting in the next five years because, in order for genetic algorithms to be successful, we have to be able to simulate an environment enough to make it realistic to where the real-life exceptions aren't going to ruin what you come up with. But for me, looking at the ability to optimize, say, a manufacturing process or the design of material, or an entire factory itself is all about how well can we realistically simulate? So, some of my research right now is looking at current VR environments and looking at the small use cases where we can use that. Because if you can do that, for one thing, genetic algorithms often create creative solutions, which to me is exciting because artificial creativity is really an interesting topic. But it can create these novel solutions that are so far beyond what we would have done with all of the assumptions that are constraining us. It has no assumptions because it goes wherever it needs to go to optimize what you set up. But the other thing is, if we can make this more widespread or even where we can do it today, what you're essentially doing is you're creating time. You're stopping time. You're going through millions of different scenarios. It's like the movie Groundhog Day. And then when you start again, you have this knowledge and intelligence that would have created, potentially, years or decades or even be impossible. So, to me, it's the closest I've seen us come to be able to create time, to create this little pocket dimension where we have this infinite time, where we can run through and make all these mistakes and get our answer and then come back into the real world with the answer. And I see the simulations that have happened and the fact that today we can use it more and more. And I see where that will be in five years. And I'm very excited about that.

Marcel**:** That's probably also where you will need different hardware, is it? To actually run like a million times more or even more scenarios in parallel?

Nathan: I think so. And some of the physics-based simulations where you teach a little mannequin doll how to walk from scratch, that's being done today and can be done. But as Alexander said, there's so many smaller details that on the surface, something seems very simple and our confidence is highest when we look at it on the surface. And then, we get depressed once we see all the details and realize how complex it is. That will take massive amounts of computational power to accurately simulate. But I also see that helping and that's where I'm looking into quantum is for that sake. On can we accurately simulate an environment enough where you can create a million years' worth of training, at a factory level, to optimize where the manufacturing sells, where the supply chain flows, where the different types of skills you need—can we come up with that? Do we have enough detail to do that without making a major mistake because we didn't build in some assumptions?

Marcel**:** Awesome. Thank you. What's your view, Alex?

Alexander: As I said, I'm an analytical dummy, so I need to come more from the business side. And what's really exciting for me is, and we are in kind of initial conversation with numerous customers, when we talk about sustainability goals and with the whole net zero emissions strategy, carbonless products, all these kinds of things. All manufacturers, or lots number of manufacturers either have to change their products, their processes or the machinery, whatsoever. And in the past, they've done that typical engineering, "Okay, we design that. We do a little bit trial and error, and some test runs. And then, over time, we ramp up slowly." If you have a couple of thousand different products, you can't change each and every product in the traditional way. And this is where I see a huge application where you can probably cook similar products, learn from the other ones, apply it to similar products to really reduce that ramp-up time significantly. Because this will be a big, big task across all manufacturers in the next couple of years. And this is where I see a big, big opportunity to make it smart right from the start using AI and machine learning.

Section 8: Wrap up

Marcel: I think that's really awesome. And that ties back right to where we started, this whole Power of Unified event with some critical drivers that are influencing manufacturing companies and sustainability being one of the top two or maybe three of them. Really important together with global supply chain disruption and all sorts of political things. So, thanks for making that full circle. And I will come back to both of you in a minute, asking you to reflect, like round off, wrap up your view on this conversation.

I really enjoyed the conversation. I will start by thanking you for being here because I don't want to forget that in the end. So, thank you for having been here. It was really interesting. And I also see from the chat that people really like that. I think we touched upon a lot of subjects like, you know, what's holding organizations back and how can you improve? What's the future? Is the future actually that simple that it'll go all we build in actual applications? Well, maybe for some transactional stuff but not for, you know, where rubber meets the road, for everything is different, and you're writing your manufacturing processes. Unless you can apply quantum theory and genetic algorithms and mimic parallel universes like a billion times and then actually learn out of that automatically. I think it's really interesting. It's been really hands-on and very far looking forward at the same time. So, thank you for that.

What's your take? Alexander.

Alexander: I could continue this conversation for hours. It was really a pleasure and thanks a lot for inviting me. And it's a good topic, and it's also interesting to see Nathan coming from a different angle. But at the end of the day, we have the same experience and the same, I guess, ideas about making a success with our customers.

Nathan: And I agree. I think it was refreshing to see your perspective. But to see that, it's critical to make sure that, you know, we talk about AI. But really, we're talking about solving problems, and that means involving the people who are working on these problems from the start. But then, unleashing imagination to see, from today, what problems can be solved today? But what does that far-reaching future look like? And then, what do we need to do in order to get there?

Like you said, one product at a time. That's not going to cut it. But look at the opportunity, if we look at this whole systematic roadmap to get there, that's going to involve people, data, AI. It's going to involve all of those things. And the real thing at the end of it is, you need to have a vision. And for me, the 20/20 vision of emissions-free aviation is the only thing that drives the work that I'm doing. If it doesn't directly contribute to that, I don't do it. And I think that's important too, that we all have this common goal, whatever it is, that this is the real problem we're trying to solve. And then there's a lot of things in between where the business has to make money, and we need to treat each other right. But we have to be driving toward something.

Marcel: I think that's it. That's wonderful. Thank you again. Thanks for joining. I think it was a wonderful conversation. Thanks to all the people in the audience for joining. All I can say, I hope you liked it. I definitely did. And I'm looking forward to another time and meeting you guys in person.

Nathan: Agreed.

Marcel: Okay.

Alexander: Okay.

Nathan: Thank you.

Alexander: Thanks to the audience.