ReRoPro

ReRoPro: Re-use of robotic data in production through search, simulation and learning

Report covering Deliverable 1, 2 and 3

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Content: This deliverable contains descriptions of the four use cases analyzed in ReRoPro and suggestions for data structures that are able to cover the main components to be stored. In addition, for each use case, associated learning problems as well as data sensitivity issues are discussed. By that, the report covers the deliverables D1, D2, and D3.

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Indhold

Public summary: Robot-database project at SDU aims to become a gamechanger for robotics

The reuse of robot data would make it much easier to improve existing or set up new robot solutions. This is the aim of the ReRoPro project. A robot database could save time and money and would also allow for smaller-scale productions to use robots. Although it sounds simple, unfortunately, it is everything but simple.

ReRoPro is a collaborative project between University of Southern Denmark, University of Copenhagen, and University of Aalborg with the companies Rockwool, Novo Nordisk, Nordbo Robotics, and WellTec as partners aiming to establish a robot database. Now the first and exploratory phase of the project is over, and the researchers are applying for funding to continue their work.

ReRoPro is about reusing robot data to improve production processes, but also to find new robot solutions in shorter time. That is a big problem, in particular for SMEs (Small and Medium sized Enterprises): It takes a lot of time to establish an assembly solution. One usually needs to start from scratch. But if one could make efficient use of data from earlier robot solutions, one could set up new solutions faster and cheaper. The problem however is that this data is in the head of people. It is not digitalized. Until now.

The idea is that when you have a certain task that you want to automate, you can type in some keywords and the information from earlier similar productions is displayed to you. Right now, there are no established structures for the reuse of data within robotics, not even within companies.

*That is to a large degree b*ecause robot data is complex. In other fields, like computer vision, big databases and neural networks are very successful, because the data is homogenous. It's images, for instance. But within robotics you have all sorts of different data; you have images, trajectories, force vectors, information on different materials, CAD-files and so on.

But this is only one of the challenges. One also needs to make an interface that is intuitive so that it is easy to sort out the information you need from the information you do not need. Another challenge is once you have the right data, how do you reuse it for your specific task. There is no standardized way of organizing data.

But do companies really want to share their robot data in a huge database that other companies, competitors as well, have access to?

Yet another challenge is that companies do not really want to share their robot data in a huge database that other companies, competitors as well, have access to. It is kind of contradictory. On the one hand, the more data that is available in the database, the more powerful it would be and the more use of it companies would have. But, on the hand, it is valuable and sensitive knowledge for the companies and obviously, companies are reluctant to make that accessible.

There are different ways to go about that. One solution could be that one only develops a database structure that can be used by companies to reuse data within their own organization. Alternatively, one could make a system where the sensitive details are hidden, but where the data is still valuable for others.

In ReRoPro project we analyzed the problem at the example if four use cases provided by the involved companies and by means of an international workshop with experts from industry and academia. The next step will be to apply for funding for establishing software structures that allow for the reuse of data.

I Introduction

The aim of the ReRoPro project was to analyze the state of the art in reuse of data in robotics in terms of common practice at companies and available software solutions. We derived ideas for a database structure, the associated learning problems, and data sensitivity issues connected to the four use cases investigated in ReRoPro provided by the involved companies Rockwool, Novo Nordisk, Nordbo Robotics and Welltec. This was achieved by three physical meetings (see schedule and dates of the meetings in appendix A) and three online meetings. In addition, a workshop with the title "International Workshop on Re-Using Robot Data" was held on 8.9.2022 where the needs of industry, current solutions, and the scientific and technical challenges that are connected to the problem of efficient re-use of robot data were discussed.

Originally it was foreseen to write three deliverables D1-D3 on the data storage structure (D1), the learning problems (D2) as well as the data sensitivity issues (D3) connected to the use cases. It was however decided to combine these three deliverables in this report to ease reading (because of the many dependencies between deliverables). The fourth deliverable on a fundraising suggestion will be presented as a separate document.

The report is structured as follows. We started the project with a questionnaire to get a systematic approach to the individual use cases. The results are presented in section 2. In section 3-6, we present the three use cases, the relevant data structure, possible learning problems and data sensitivity issues associated to the individual use cases. In section 7, we perform considerations about the data structures across use cases. Part of the project was the "International Workshop on Re-Using Robot Data" held on September 8, which is shortly described in section 8, where we also dwell on the media work, we performed during the project.

2 First Approximation: The questionnaire

The main idea behind the questionnaire was to gather information and identify synergies of data generation and re-use taking place in the involved partner companies. The questionnaire included the following topics

- Company information,
- Storing data – current state in the factory
- Data re-use – current state
- Data sensitivity
- Potential use case

In the questionnaire, the partner companies provided information outlining the current state of the data re-use. Some of the questions and results are provided in the following. Furthermore, the entire questioner and the results can be found in the Appendix B.

1	Fast setup of robot tasks and speedup the development of new tasks e.g., gripper fingers and fixtures.
2	N/A
3	Reduce lead time for development and implementation of the new lines but also using for predictive maintenance for better performance. so time is the most crucial factor
4	It could several things, but within surface treatment applications such as sanding, grinding or polishing: - speed up robot programming time - optimize cycle time and end result - reduce material waste
5	In the future, we would like to store images to develop more AI models to further optimize - replacement of complex and/or manual tasks, improve safety
6	to minimize our time spend on programming the same data over and over again.

Figure 2.1: Purpose of data re-use provided by the project partners

In Figure 2.1, the purpose of data re-use as foreseen by the project partners is provided. It covers the reduction of set-up time, predictive maintenance and process optimization.

	Robotic state data (joint positions, trajectories, etc.)	4
	Camera feed (2D-data)	2
	3D data (lidar, depth camera)	1
	CAD data (parts)	4
	3D spatial layout of production process	2
	Process data (machine data)	4
	User specific data (i.e., data, manually provided by user)	4
	Other kinds of digital models	0
	Other	

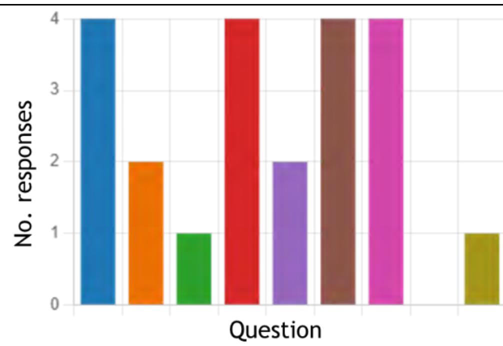
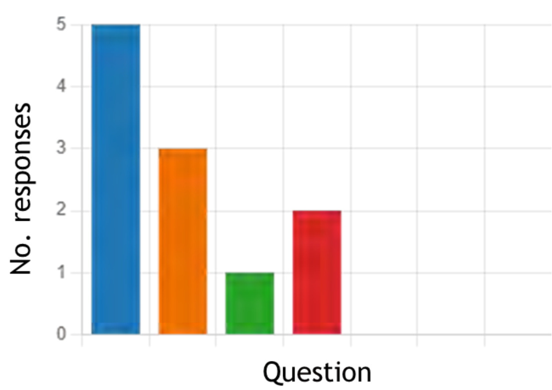


Figure 2.2 Use-case data type

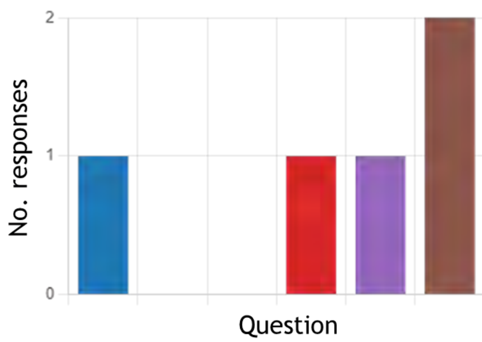
Figure 2.2 shows different data types that are supposed to be represented in the database. As expected, we see a large variation of data types that makes the problem in particular difficult.



	within the company	5
	with selected partners	3
	customers	1
	suppliers	2
	resellers	0
	with the world	0
	Other	0

Figure 2.3 Who would it be ok to share the data with?

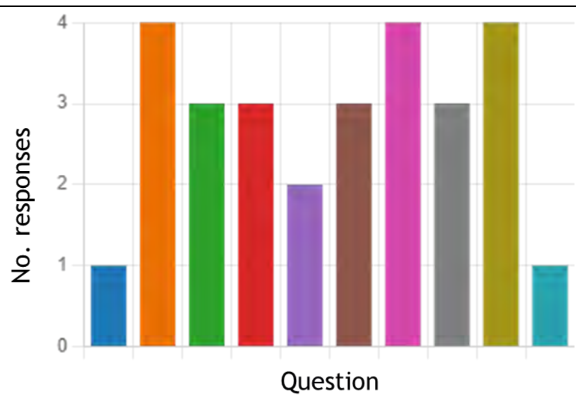
Figure 2.3 addresses data sensitivity. As expected, companies are very protective about the data and are only willing – if at all – to share data in a small circle.



	Speed up of the production process	1
	Speed up of the set-up of new/changed production processes	0
	Increased reliability of the production process	0
	Improved performance compared to human operator	1
	Increase quality of produced items	1
	Other (Improve safety)	2

Figure 2.4 How would you measure the success of the data re-use?

Figure 2.4 addresses the success measure of a final application of data re-use. Speed-up of processes and quality increase are here in the focus.



	analysis of your production processes	1
	the improvement of production processes	4
	condition based maintenance	3
	predictive maintenance tasks	3
	documentation and traceability	2
	to develop new production processes	3
	speed-up the installation of new production processes	4
	product development	3
	simulating your processes	4
	Other	1

Figure 2.5 Do you use your data for …?

Figure 2.5 describes what the data is supposed to be used for. We see wide spectrum of possible applications where the speed up of the set-up as well as the improvement of the production process are most important. Companies are also interested in using simulation to achieve that.

Based on the questionnaire, we see indications that there are quite some synergies between the companies and the use cases they are providing, but not too many. One of the conclusions we made is that in the current state, the companies are not reusing data to benefit the production, but they use it for quality monitoring and statistics. The information collected in the questionnaire gives an indication that there is a large potential for the re-use of data and that the companies are interested and willing to invest in the idea of exploiting data for optimization of their processes. Of course, since we only used four samples in our investigations, we need to be careful in generalizing our results. However, we think they gave some indications that were also confirmed at the international workshop organized in the project.

3 The Rockwool use case

3.1 The use case

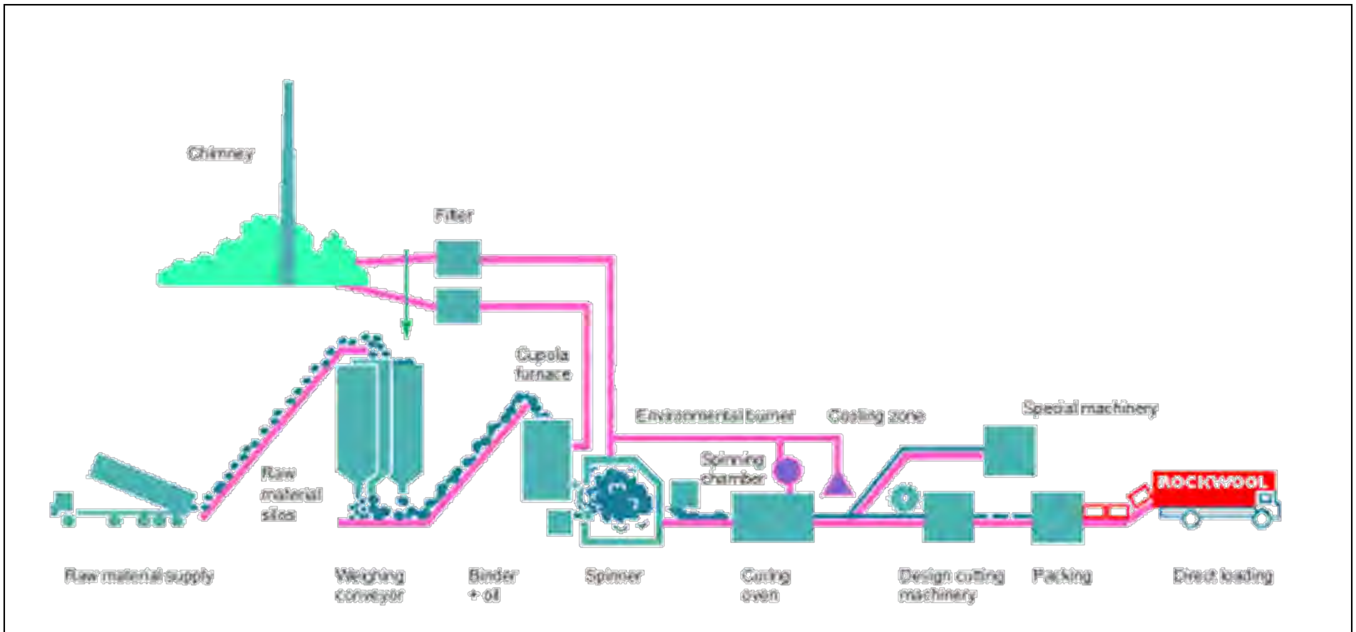


Figure 3.1: The Rockwool production process

The technological use case provided by the factory is to robotize the procedures for cleaning the spinner deck in the production line, which is normally done by operators. The spinner deck (in the middle of the production process as shown in figure 3.1) is a tough and dangerous work environment with melting splashes, high heat, and noise. The requirement for cleaning of the spinner chamber is to let it cool down so that an operator (usually provided by an external company) can proceed with the cleaning step. To do so, the operator is exposed to environmental conditions which are not human friendly.

The proposed idea for tackling this challenge includes a digital twin of the process consisting of a robot, water jet head and high-pressure pump. Furthermore, a similar solution can be applied for checking or cleaning the cyclone and spinner chamber trays, tapping of the furnace or general inspection of the process in inhospitable areas with computer vision, which is dangerous and usually performed by human operators.

The benefits for the company when applying a robot solution are the following: increased safety, reduction of near misses and incidents, reduction of cost for external contracting to perform the cleaning operation and improvement of the end product quality, with more frequent cleaning.

3.2 Data structures

In terms of data re-use, the following data can be generated and stored with the proposed use case:

- Robot data (joint positions, maintenance data, energy consumption, tool space trajectories, robot workspace monitoring, time series trajectories, force/torque data): all presented as numerical data.
- Visual feedback (depth data, images, laser range finders, 3D point cloud of the chamber): presented as 2D and 3D matrixes as well as point clouds.
- Production data (Point of Production data (POP) (Spinner related production data such as motor speed, current drawn by motors, temperature of cooling water): all numerical in time series format.
- Quality control data (3D point cloud of the chamber, quality of the end product linked to the cleaning of the chamber (production parameters): presented as 2D and 3D matrixes, point clouds, numerical time series data and manually provided text.

The outlined data can be recorded with an update frequency of 10 – 500 Hz and then down sampled to be stored in an sql, mongo or AZURE blob storage database. Already today, some of the data generated by the production machinery, e.g., spinner drum, is used for analytics (mainly sensor data) and vision data for quality inspection.

3.3 Relevant Learning problems

We could identify three learning problems that were in particular relevant for this use-case:

LP1: Predictive maintenance based on the process data.

- Correlations study between the rejects at the quality control station, input raw material, production parameters and the frequency of cleaning the chamber.
- Out of the data, a model can be learned and transferred to other Rockwool production sights.
- In terms of the use-case: when is the right moment to shut down the plant and start cleaning the production line?

LP2: Correlation between the slag formation, production parameters and quality rejects and dirt level pose estimation:

- Recorded process quality data is used for learning a deep network which can generalize and act based on the input parameters.
- Dirt formation in the spinning chamber is monitored by cameras, the images will be trained to classify between the different amount of dirt levels, afterwards the robot will be engaged to clean.
- 3D point cloud will be trained to localize the build-up on the wall. Cleaning will be engaged, which can lead to more optimal exploitation of production and service intervals.

LP3: Robot based learning challenges

- Robot trajectory learning, from demonstration / simulation and iterative learning on the process level for trajectory optimization.
- Visual feedback connected to robot control.
- Path planning based on previous executions, iterative optimization of the robot trajectories.
- Energy consumption optimization based on the recorded data.
- To achieve this, a digital twin of the process should be realized.

3.4 Data sensitivity issues

The company considers information on their production processes as confidential information. This includes process data, quality control data and robot data. Therefore, the reuse of data is in the outset constrained to reused within the company. Per use-case it might be able to apply aggregation tactics. E.g., for an equipment manufacturer to aggregate operation data so it does not reveal information about the overall production process but only provides an operational understanding of the equipment, e.g., for predictive maintenance.

4 The Novo Nordisk use case

4.1 The use case

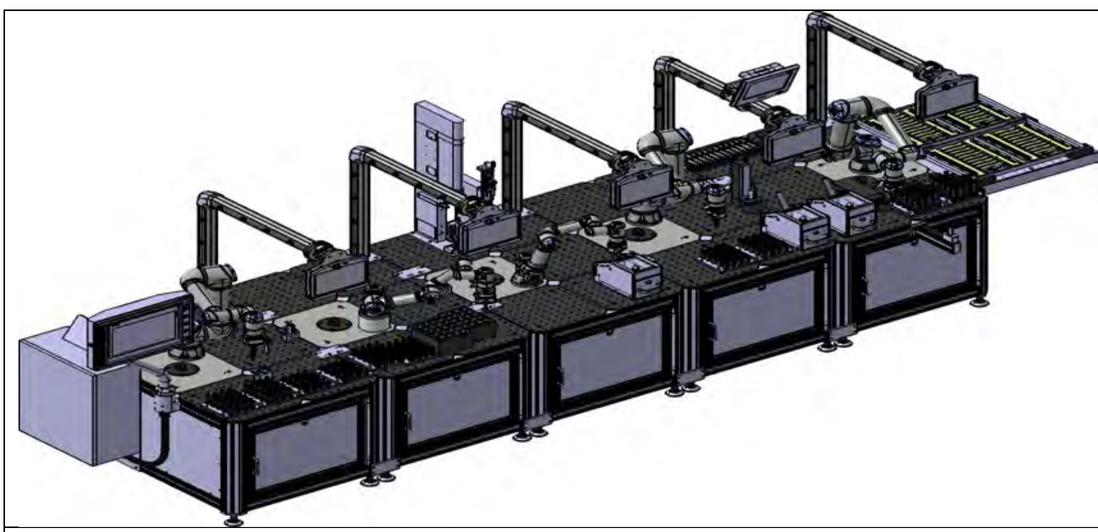


Figure 4.2: The assembly line

The objects to be assembled are injectable devices (see figure 4.1). An injectable device contains ca. 10 pieces which are assembled by different operations (e.g., injection, screwing, dropping) and for which at different stages verification procedures based on vision, height or force information are required. On a product level, hundreds of millions of injectable devices are produced, this however is not done by robots but by machines specifically designed for the particular injectable device. However, to achieve highest quality, smaller batches of hundreds of thousands units are produced and several verification tests are performed. This is done in different iterations in which the product can still be mildly changed. To produce these units, Novo Nordisk uses an assembly line with between five to seven individual robot stations (see figure 4.2) where objects are passed between stations mainly via fixtures.

Figure 4.1: One example of an injectable device

In the context of the ReRoPro project, this use case is ideal, since the different versions of injectable devices differ only slightly. Hence knowledge about, e.g., grippers, fingers, fixtures, trajectories and verifications can be quite easily transferred across different versions of injectable devices.

The overall process from concept to product can take 4-5 years, the production of the units for clinical testing can take up to a year. To speed up this process, a fast set-up of the assembly line – which now can take up to half a year – is crucial. Hence in this use case, we primarily focus on reusing data to speed up the set-up of the assembly line. The main bottlenecks in the long commissioning phase are the programming of line as a whole, PLC, the verification programming and in particular the design of fingers and fixtures.

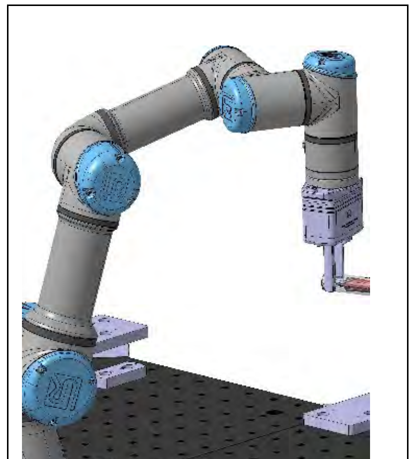


Figure 4.3: Grasping with a finger specifically designed for a particular object

4.3 Data structures

The use case represents a rather typical assembly problem with a lot of similarities to assembly problems in other SMEs in terms of the number of pieces and the kind of assembly operations involved. Important pieces of information connected to different subtasks that should be stored are the following:

Grasping process: Grasping usually requires the production of fingers that are specifically designed towards a particular object and a specific grasping pose (see figure 4.3). In an ideal world, the same finger could be used for different grasping poses (which depend on the subtask) or objects. It is possible to learn such fingers in simulation (Wolniakowski et al. 2017). For that, the object trajectories, the grasping pose and the CAD model of the object and grippers together with some quality information about the grasping process (e.g., the number of interruptions of the assembly process caused by issues associated in particular to grasping) should be stored.

Figure 4.4: Example of a fixture

Fixture design: Similarly - but in most cases easier than for gripper design -, fixtures (see figure 4.4) need to be designed for each particular object. Also, here object trajectories, the grasping pose and the CAD model of the object and fixture together with some quality information about the handling process should be stored.

Quality control data: During the assembly process different verifications are performed. For the particular use case, this concerns height measurement of the relative distance between two components to ensure they are in the right position (and that the dose of the device is correct, hence patient safety), two force displacement trajectories to check two snap functions (see figure 4.5) occurring when to sub-objects become assembled as well as a vision-based control of at snap function.

Robot Data: Data about internal parameters gathered during the production process can help to monitor and improve the functionality and performance the assembly line but also for predictive maintenance, when trying to spot high likelihoods of possible errors (due to, e.g., robot wear-off) before such errors actually occur.

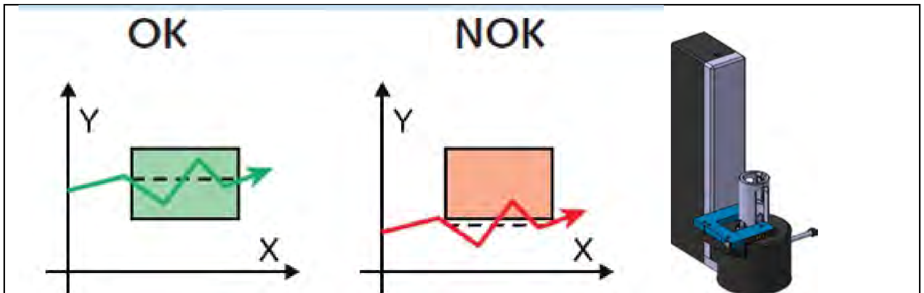


Figure 4.5: Left Good and bad example-trajectories for the snap function. Right: Apparat that measures the snap-function trajectory.

4.3 Relevant Learning problems

We have identified the following four learning problems (LP1-LP4), for which data could be re-used:

LP1 Gripper and fixture design: For the task of designing a gripper for a new object, a similar object could be found in the database together with the associated grasp pose, the finger and the trajectories. This could serve as a starting point for designing or learning a new finger, for example by simulation (this can be done similarly for fixtures). In this context, designing the fingers (possibly able to grasp multiple objects or the same object with different grasp poses) is a particular challenge.

LP2 Learning an acceptable range of force displacement trajectories to check the snap functions: Today what is acceptable and what not is defined manually. Based on the observed data, such ranges could be learned, e.g., by a classifier based on a neural net.

LP3 Indicating possible robot failures before they occur (predictive maintenance): Based on monitored robot failures and data that has been gathered before the failures occurred, wear-off of hardware can be detected and robots can be repaired or exchanged before errors can occur.

LP4 Optimizing of overall performance of platform: Based on production data, the flow of the overall process can be monitored and individual parameters adjusted and their effect evaluated.

4.4 Data sensitivity issues

Again, data on the process is considered confidential. However, in this case confidentiality also cover the specific product design. Tactics can be applied that constrain the access to information about the specific product design. E.g. by mutating specific parts of the design in a manner that still allow to design grippers or design a gripping procedure.

5 The Nordbo Robotics use case

5.1 The use case

Nordbo robotics provide tools for easy programming of sanding and grinding operation (as shown in figure 5.1). The end-users and integrators must make several choices when deploying their solution in practice, e.g., what adhesive to use and how often to replace it. These decisions involve trade-offs between cost, quality, and efficiency. The decisions could become easier for their customers if Nordbo could provide data-driven suggestions for what decisions to make. Three functionalities have been identified:

Figure 5.1: One of the NordBo Robotics use-cases

F1: Estimate which instance (a concrete tool) in a tool category (e.g., rotational sanding) provides the best performance (e.g., lowest cycle time or best quality for a task).

F2: Estimate for a given task and tool what adhesive to use to obtain the best performance (e.g., lowest cycle time or best quality for a task).

F3: Estimate how often the adhesive must be replaced to provide the required minimum quality.

5.2 Data structures

The data needed to provide these functionalities includes the following data:

- Production data - Type of material (F1) – String
- Production data – Type of finishing (F1) - Numerical
- Process data - Level of finishing (F1) - Numerical
- Quality control data – Quality of finishing (e.g., on a categorical scale) (F1) - Numerical
- Robot data – Area treated (F1) - Numerical
- Robot data – Total force use (F1) - Numerical
- Robot data – Cycle completion time (F1) – Numerical

During the collection some of this data needs to come from the user to provide relevant metadata about the system setup, e.g., choices for tools and adhesives. The data would be collected in the resolution provided by the cobot and tools (up to 500 Hz in the case of UR). However, the data might need to be down sampled given the limited storage on a cobot as in 1 h approximately 403 MB would need to be stored. This would be new for Nordbo as they today only store a small subset of such data and only store this in flat files. The data is only considered sensitive by the customers and Nordbo and therefore today is only collected on the cobot.

5.3 Relevant Learning problems

Based on the collected data three learning problems have been identified to support realizing F1-F3.

For F1, a learning method should estimate which instance (a concrete tool) in a tool category (e.g., rotational sanding) provides the best performance (e.g., lowest cycle time or best quality for a task). This requires to learn an estimator from the input data that includes the tool, tool category and metric to optimize, and that outputs a ranking of potential tools. Until enough data is available an expert-configured rule-based estimator could be used to kickstart the process.

For F2, a learning method should estimate for a given task and tool what adhesive to use to obtain the best performance (e.g., lowest cycle time or best quality for a task). This requires learning an estimator that receives the task, tool and quality metric as inputs and outputs a ranking of adhesives to use. Until enough data is available also here an expert-configured rule-based estimator could be used.

For F3, a learning method needs to estimate how often the adhesive must be replaced to provide the required minimum quality. This requires learning a predictor that takes adhesive and any relevant context parameters as input and output a prediction of the level of quality over time.

5.4 Data sensitivity issues

The Nordbo case also represents a case with confidential process data. Here data could be reused if aspects of the process that is considered confidential can be removed, e.g., via aggregation. Another option would be to consider the method of federated learning so only the learned model is shared not the detailed data.

6 The WellTec use case

6.1 The use case

WellTec is a company that, among other products, produces Well Tractors that can carry out operations throughout the entire length of the wellbore regardless of the deviation and extension of the well. In open hole wells, the Well Tractor can apply the force required to push large tool strings as well as navigate past washouts. It enables operators to extend the reach of traditional e-line deployment into highly deviated and horizontal wells, making it one of the most cost-effective and successful applications for deployment in well interventions.[1]

A significant part of WellTec's production is based on Computer-Aided Manufacturing (CAM). CAM programming is the process of developing programs for CNC machines, such as milling and turning machines, to produce parts. A 3D model of a part is typically imported from Computer-Aided Design (CAD) software and the production process, including tool configurations, trajectories, and simulation, is then defined in the CAM software (see Figure 6.1 and 6.2).

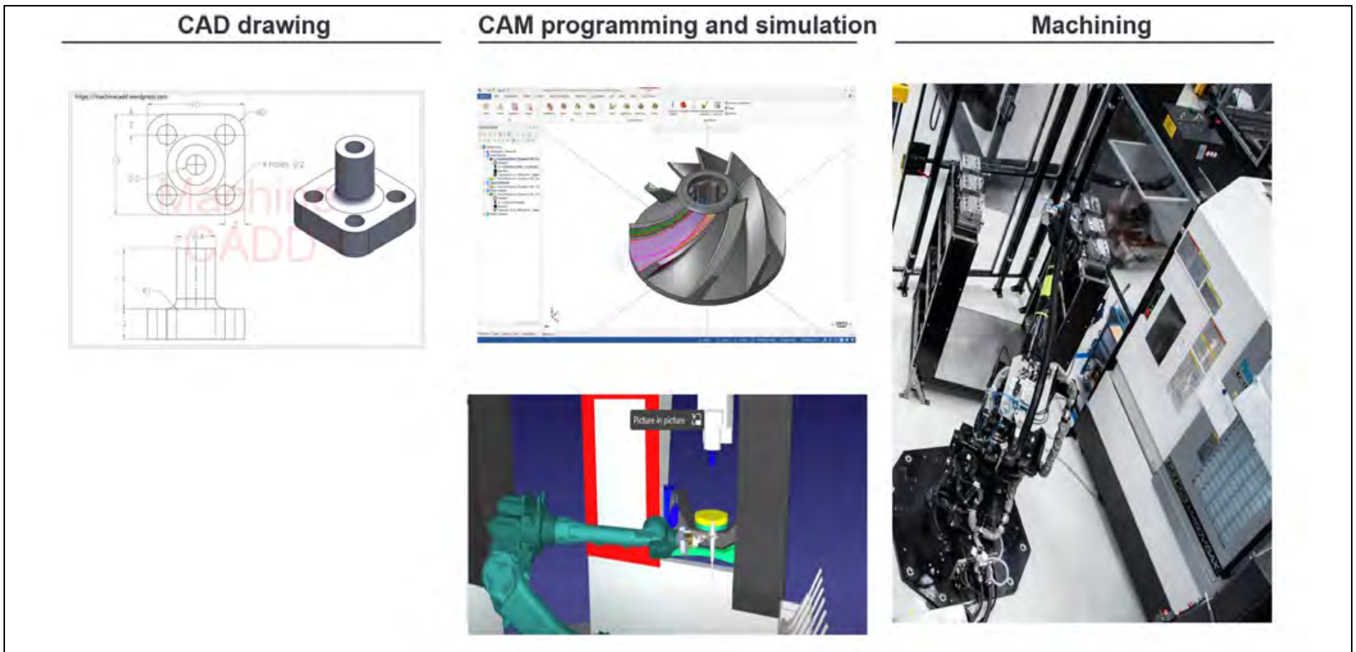


Figure 6.1 - Parts production process. First, a CAD drawing of the part is done, then CAM programming and simulation is performed before the part is machined.

A CAM program consists of a number of operations and many operations are complex in the sense that the programmer must specify a number of parameters, such as cutting method, distances, and angles. An example can be seen in Figure 6.2.

[1] From https://welltec.com/products-landing-page/well-tractor/well-tractor/

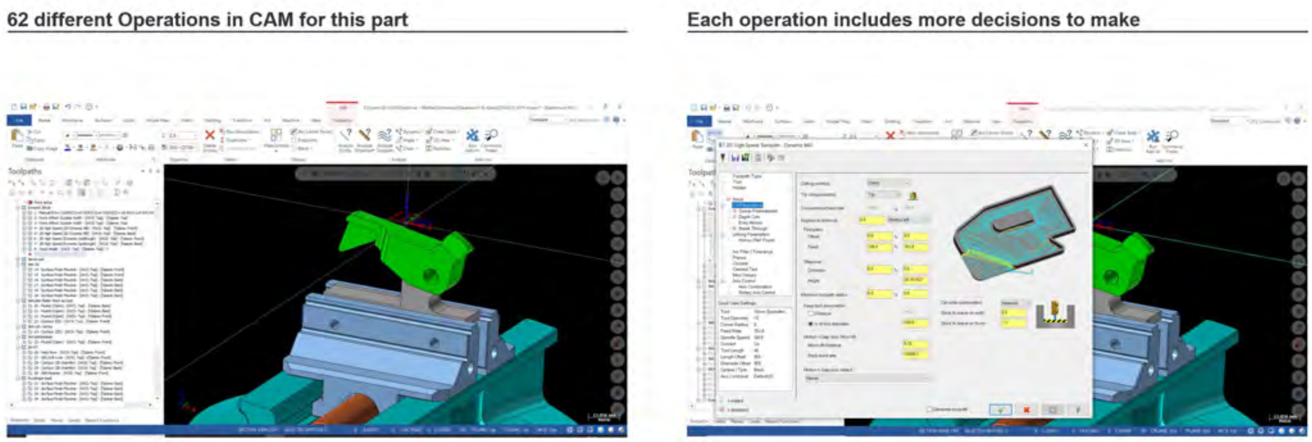


Figure 6.2 - Example of a CAM program for a part. The program consists of 62 operations (left). Operations are typically complex and require careful selection of parameters (right)

WellTec has a catalog with over 5,000 parts, see examples in Figure 6.3, many of them are similar, but not identical. For each part, a significant portion of a CAM program needs to be done manually by an expert which is costly and tedious, even though many parts are similar and even share identical features.

Figure 4.3 - Examples of WellTec parts. Many of their 5,000 parts are similar, but not identical.

WellTec would like to reduce the effort associated with creating CAM programs by exploiting the fact that many parts are similar but not identical. Simple templating is not sufficient: the big step lies in recognizing previously programmed geometries.

6.2 Data structure

The data available is:

(i) the CAM programs,
(ii) the CAD models.

WellTec currently has more than 5,000 CAM programs each with an average of approximately 75 operations.

Both CAM programs and CAD models are stored in proprietary file formats, but the software used for the CAM programs, Mastercam, does allow plug-ins to get access to the program, such that some form of export to a text-based standard format, e.g., JSON, YAML, XML or similar, should be possible. As there are several open CAD formats, there is a good chance that the 3D models of parts can be saved in a readable format.

Based on the 3D CAD models and the associated CAM programs, the goal is to store the data in a format that enables efficient queries for similar parts and individual geometric features and obtain the corresponding CAM operation(s) for that part. Once such approach could be based on multi-resolution voxel geometry, but its the similarity measure cannot be based on geometry alone but must also take into consideration similarities (or distances) in the CAM operation space as small CAD model differences can lead to significantly different CAM programs. The geometric representation, queries and similarity measures are thus important topics for further research.

6.3 Relevant Learning problems

There are several interesting learning problems whose solutions could help to significantly reduce the manual work required to produce new parts:

- Learning representations of 3D shapes that enables relevant and efficient querying for similarities between parts and sections of parts.
- Identifying similar or identical geometries (see Figure 6.4 for an example) and learning the impact differences have in CAM programs.
- Enabling data-informed templating or data-assisted CAM programming (similar to GitHub co-pilot)
- Automatic evaluation of manually or similar manually designed CAM programs
- Fully automated CAM programming based on input CAD model (ideal).

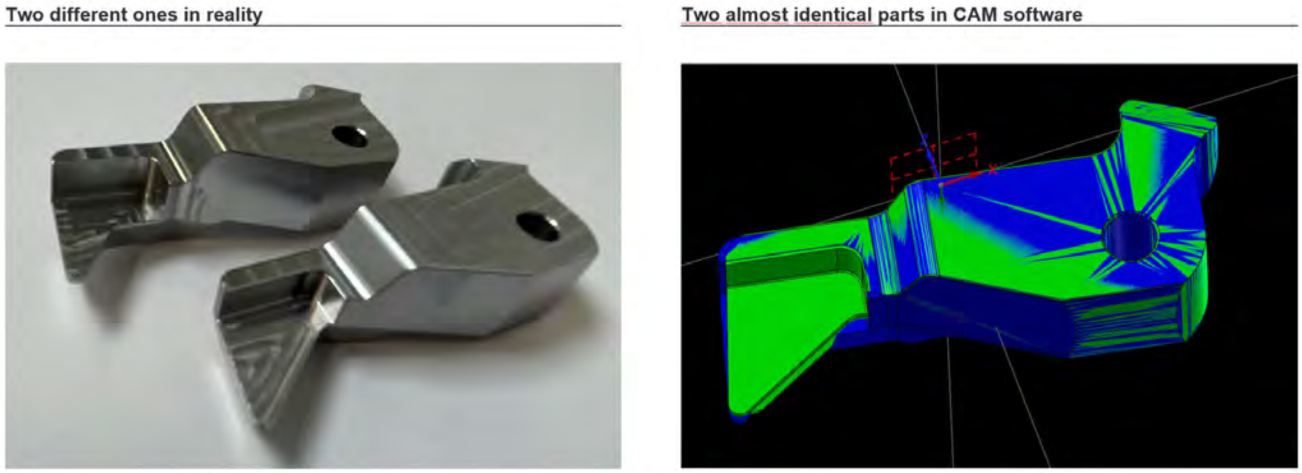


Figure 6.4 - Two similar, but not identical, parts in reality (left) and their CAM software representations in blue and green overlaid (right)

6.4 Data sensitivity issues

The primary sensitivity issue in this case is the specific product design. Again, limitations can be implemented to the access to specific parts of the design. E.g., mutating specific parts of the design that still allow to program the production process for the specific part.

7 Considerations about the date structures across use cases

The four use-cases that have been investigated in the ReRoPro project were of very different structures. The Rockwool use case is currently not automated at all; hence a completely new design of robot solutions would need to be generated. The Novo Nordisk use-case is a typical assembly problem, where many very related assembly problems with only small deviations can be addressed with a similar basic hardware structure. The NordBo Robotics case includes a significant learning by demonstration aspect. For these three use cases, robot data is not yet systematically gathered. Very different it is in the Welltec use case, where masses of data in terms of programs and CAD files do exist.

We also have seen a large variety of data content that needs to be stored which underlines the inhomogeneity problem discussed before. From that, we can conclude that any data structure that is realized needs to be extendable such that new use-cases in their specifics can be addressed. Trying to define *the* data structure will be counterproductive. One probably also has to think about rather “loose” content-based search structures where the human will still have a strong role in combining the found bits and pieces into a functioning assembly solution.

8 The International Workshop on Re-Using Robot Data on September 8, 2022

At the "International Workshop on Re-Using Robot Data" (https://direc.dk/international-workshop-on-reusing-robot-data/), held on September 8, 2022, at SDU, the needs of industry, current solutions, and the scientific and technical challenges that are connected to the problem of efficient re-use of robot data were discussed by national and international experts from academia and companies.

The workshop was organized in four sessions "The ReRoPro Project", "Data-Re-Use in Industry and Science", "Industrial perspectives" and "Future perspectives". Prof. Michael Beetz from the University of Bremen and Dr. Markus Rickert from the Technische Universität München were invited speakers. The workshop was funded by DIREC and DDSA and supported by MADE (made.dk) in terms of media support.

In total 68 participants from academia and industry attended the workshop. This large amount of people could be gathered because of an extensive media work (besides using the channels provided by SDU, MADE and DIREC also an article in Ingeniøren[2] and jernindustri.dk[3] appeared).

The large attendance at the workshop shows the importance of the problem addressed in the workshop. It also helped the ReRoPro consortium to establish an overview of the state-of-the-art in the field as well as to network with new partners for a currently planned grant proposal.

The workshop addressed a problem that is positioned between the field of data science and the field of robotics. Hence the workshop allowed these two communities to exchange ideas on how to approach the problem of re-use of robot data and connect for further fundraising.

The event was a big success. It would be appropriate to repeat such an event to monitor the progress in the field on that important topic. This hopefully will be done within the planned follow-up project of ReRoPro.

On a slide, on which we tried to conclude the workshop, it was stated:

- There is no good software solution for the re-use of robot data on the market
- Companies tend to store robot process data not at all or locally in excel files
- Three technical issues to be addressed
    - Finding a structure that covers the inhomogeneity of data connected to robot assembly solutions
    - Define ways for reasonable queries
    - Intuitive interface
- Link these queries with the simulation of the assembly problem
- To address data sensitivity is crucial
- Solutions that are out there are very complex and do not address robot data in its full complexity
    - There are of course attempts to address these issues, but they are not yet available as products
- Note that SMEs might have other demands than large companies

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[2] https://ing.dk/artikel/klar-deling-genbrug-software-rydder-robotters-enorme-datamaengder-260207
[3] https://www.jernindustri.dk/article/view/854397/professor_vi_skal_genbruge_robot_og_automationslosninger

9 Conclusion

The ReRoPro project gave valuable insights into a very relevant problem that lies at the interface between Robotics and AI. The large number of attendencies from academia and industry indicated the urgency of the problem. With the ground work we performed in ReRoPro, we are now able to write a strong project application, in which the indicated issues can be addressed.

10 References

Wolniakowski, A., Miatliuk, K., Gosiewski, Z. et al. Task and Context Sensitive Gripper Design Learning Using Dynamic Grasp Simulation. J Intell Robot Syst 87, 15–42 (2017). https://doi.org/10.1007/s10846-017-0492-y