Robot Cognition in Disassembly

Advanced Information Processing for an Adaptive Dismantling Ecosystem

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***Abstract*—Disassembly is an elementary process step for efficient recycling. In order to improve disassembly operations, the implementation of digitalization technologies and advanced robotic systems is investigated in this paper. The authors propose an agent-based robotic system which is capable of classifying components in a hierarchical structure for an optimized determination of an ecologically and economically feasible level of disassembly. By utilizing a machine-learning classifier, an adaptive system is facilitated being able to react to the dynamic change of conditions in the reverse supply chain. Holistic information management processes are the foundation of the advanced disassembly system. It is shown that the application of cognitive robotics fosters the progression towards an advanced circular economy by being able to reliably classify End-of-Life options autonomously.**

Keywords—disassembly; recycling 4.0; robotics; decision making; machine-learning.

I. Introduction

Resource scarcity and the necessity of limiting emissions in order to tackle the climate change issue are hard constraints in today's manufacturing industries. Following the Sustainable Development Goals (SDGs) set by the United Nations, responsible dealing with rare materials and elaborate products becomes a strategically important objective for every enterprise [1]. Reuse, remanufacturing and recycling as End-of-Life (EoL) options seem to be mandatory consequences of this development.

However, the current situation with EoL products often shows the inability to deal with them appropriately in terms of economic efficiency and technical dexterity. A key point in all possible EoL treatment paths is the process of disassembly. Disassembly can be understood as the entirety of actions required to separate manufactured products to their modules, components or resource constituents [2]. Advanced robotic systems can provide an automation solution so that high quality component output for reuse, remanufacturing or high grade material recycling can be achieved while reducing the planning complexity for the companies and saving costs due to decreasing process time. Admittedly, the implementation of a robotic system often requires a great effort in programming for each variant which needs to be dismantled. In order to overcome this impetus, advanced cognitive robotic systems are capable of perceiving their environment through camera and sensor technologies and make decisions based on available data autonomously. The field of cognitive robotics embodies the study of knowledge representation and reasoning problems in dynamic and incompletely known environments by a robotic agent [3]. In the *Recycling 4.0* project, the authors develop an informationally integrated disassembly system by employing the characteristics of cognitive robotics to fulfil highly complex tasks, such as the disassembly of different (and partly unknown) products by the example of electric vehicle battery systems in varying product conditions.

This paper proposes an adaptive system-approach for robotic disassembly in dynamic environments. Through connecting the disassembly system to a superordinate, cloud-based information system [4], the robot is able to stream real-time information for each process step, taking different requirements of individual supply chain actors into account while constantly updating available data. A machine-learning empowered decision making process is established and presented to assist in making improved decisions for the disassembly grade in respect to economic, ecologic and social dimensions of the available EoL-options. In contrast to existing disassembly systems, such as those of Jungbluth et al. [5] and Vongbunyong et al. [6], the system actively contributes to the cloud information system and receives live data updates from various sources and system participants, making it an ecosystem adaptable to changes in the general market situation of the targeted product. Furthermore, the system is able to generalize knowledge from existing product structures so that it is able to work on previously unknown products. By scanning the product with its vision system, the robot is also able to rate the visual condition of the product as first-time hands-on experience in the recycling process-chain.

The paper is structured as follows: In Section 2, the initial problem of robotic disassembly automation is described and the research question is formulated. Section 3 introduces the concept of the agent based system and explains the methods

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proposed to answer the question based on a standardized product structure model and a feature based machine learning classifier. An evaluation of this classifier using generic product data is described in Section 4. A conclusion on the results and its contribution to disassembly as well as an outlook to future research within this project is given in Section 5.

II. Problem Statement

Disassembly operations usually include the largest number of employees and the highest complexity regarding the amount of possible variants in all EoL-treatments, making automation approaches difficult to establish in most of the contemplable use-cases. Advantages of human workforce, such as accurate perception, craftsmanship and intelligent behaviour are needed in disassembly scenarios, whereby time effort, cost and volatile quality of manual processes have to be overcome. In order to keep the required investment for disassembly automation feasible in terms of an overall benefit in cost compared to the fully-manual process, a hybrid disassembly scenario with Human Robot Collaboration (HRC) should be realized. Another benefit of HRC is the capability of implementing a correction functionality for the robotic agent in favour of enabling learning behaviour as a fail-safe strategy for the robot cognition processing.

The general requirements of a cognitive robotic disassembly system are [7]:

- Disassembly sequence planning and optimization
- Determination of the level of disassembly (technical possibility vs. economic feasibility)
- Capability of dealing with high numbers of product and product state variants
- Including market information regarding cores, resource data and component reselling
- Including life-cycle information and product data

The problem of profitability and optimal decisions exists mostly due to a lack of information spanning various participants in the EoL-value-chain. These optimal decisions cannot be made due to missing conspectus of all relevant data.

In order to locate this work within the canon of disassembly planning research, the focus lies more on disassembly decision making (in respect to multiple criteria) than the actual sequence planning depending on the product model. Feng et al. [8] presented a stage-wise decision making process on each hierarchy level, determining the EoL-option at the last stage of the process, whereas this decision marks the initial input of the proposed system in this work. Focusing directly on a robotic disassembly, Li et al. [9] presented a multi-criteria assessment with a score-system which is difficult to maintain in the dynamic environment of a circular economy with many different value-streams and stakeholders. The consideration of varying component quality and operational cost is introduced by Tian et al. [10], taking the randomness and fuzziness of real processes into account. However, such a quantified, designated assessment is often not possible due to a lack of information. Furthermore, quality level ratings would be different for various purposes depending on the market rather than technical process experience.

At this point, the *Recycling 4.0* model introduces a superordinate information marketplace which is connected to the disassembly system. All relevant data for optimized decision making can then be obtained from the information marketplace and from the robotic system's vision unit. However, anticipation from existing rules is not possible, because market principles of a full-scale reverse supply chain cannot yet be foreseen. Therefore, dynamic models which take various types of data from different sources into account need to be utilized. These forms of disassembly grade decision systems have not been implemented before. To gain a wider conspectus of the topic, the authors already conducted an analysis of a vast number of robotic disassembly automation examples which can be found in [11].

The proposed system must be able to constantly respond to changes and also show evolutionary behaviour in terms of how the adaption is performed (second-order adaption). An important foundation for the depicted approach is the information exchangeability and cross-system interoperability within the *Recycling 4.0* ecosystem. Summarized, the challenges of automated disassembly can be seen as a problem of information management along the EoL process-chain. The addressed research question of this paper therefore aims at this very point:

How can the available supply chain information, lifecycle-knowledge and sensory information be used in the disassembly process in order to benefit the overall recycling efficiency?

III. Concept and Methods

The developed concept of the robotic disassembly system consists of three different agents, each fulfilling specific requirements of the proposed tasks (Fig. 1). As an external junction, an information marketplace is established, serving as a central information node for all participants of the reverse supply chain. A presumption of the developed concept of this paper is that semantic and structural information required for the robot cognition process can be obtained from this marketplace [4].

The main module of the system is the *Robot Cognition Processor* (RCP), responsible for information synthesis and decision making regarding the step-wise decision of disassembling the product structure up to the optimized grade by economic, ecological and social considerations at the time of disassembly. The required sensory information is gathered by the *System Perception Unit* (SPU). The module captures the target object with a specially designed 3D-camera in order to identify, detect (localize) and rate the part pertained. This agent's contribution to the RCP process is an optical condition diagnosis factor which is used in addition to the product's internally assigned health factor. Finally, the *Disassembly Execution Unit* (DEU) is formed by the operative robotic system (robot arm and tooling), as well as an affiliated execution monitoring system. Based on the disassembly command of the RCP, the DEU is responsible for path planning, tooling and actual disassembly action execution. An HRC pairing of the robot and a human worker enables the

DEU to accomplish complex tasks and take instructional input of the human worker, in the case of the autonomous path planner failing to achieve its objective.

The core process of the RCP is the handling and processing of relevant information in order to make a decision compliant to economic, ecological and social objectives. After an initial decision about the general feasibility of core disassembly, the disassembly request for the target part is forwarded to the RCP. Available product data and technical documentation as well as a standardized set of relevant information are gathered from the superordinate information system. Product states from the optical assessment via the SPU are merged with the gathered information into a single attributed dataframe per object, forming a set of all available data for the target product or component. This augmented information set is transferred back to the cloud information system to make predictions about future batches of related products possible.

The next step in the RCP process is a machine-learning sub-process of step-by-step decision making along the hierarchical structure of the product. By the time of individual disassembly decision for each component, three possible classifications are taken into account (Fig. 2). Reuse and remanufacturing are clustered in one category, as they both strive for functional integrity and component resale. The

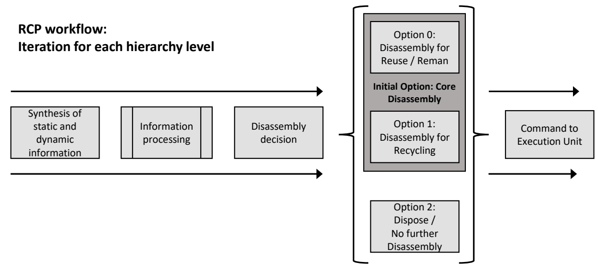

Figure 1. RCP workflow process

second option is disassembly for improved material recycling. The third option is not to disassemble any further, thereby determining the final grade of disassembly. If at any point, the system is not able to make an acceptable or technically feasible decision, human decision making and manual teaching in a possible interaction phase may give the missing input to the system, which is then learned for future appliance and adaption, improving the possible system autonomy with an increasing number of iterations and variants. The desired disassembly sequence is thereby automatically determined by the order of parts and components eligible for profitable disassembly. Physical disassembly commands are then forwarded to the DEU for path planning and execution.

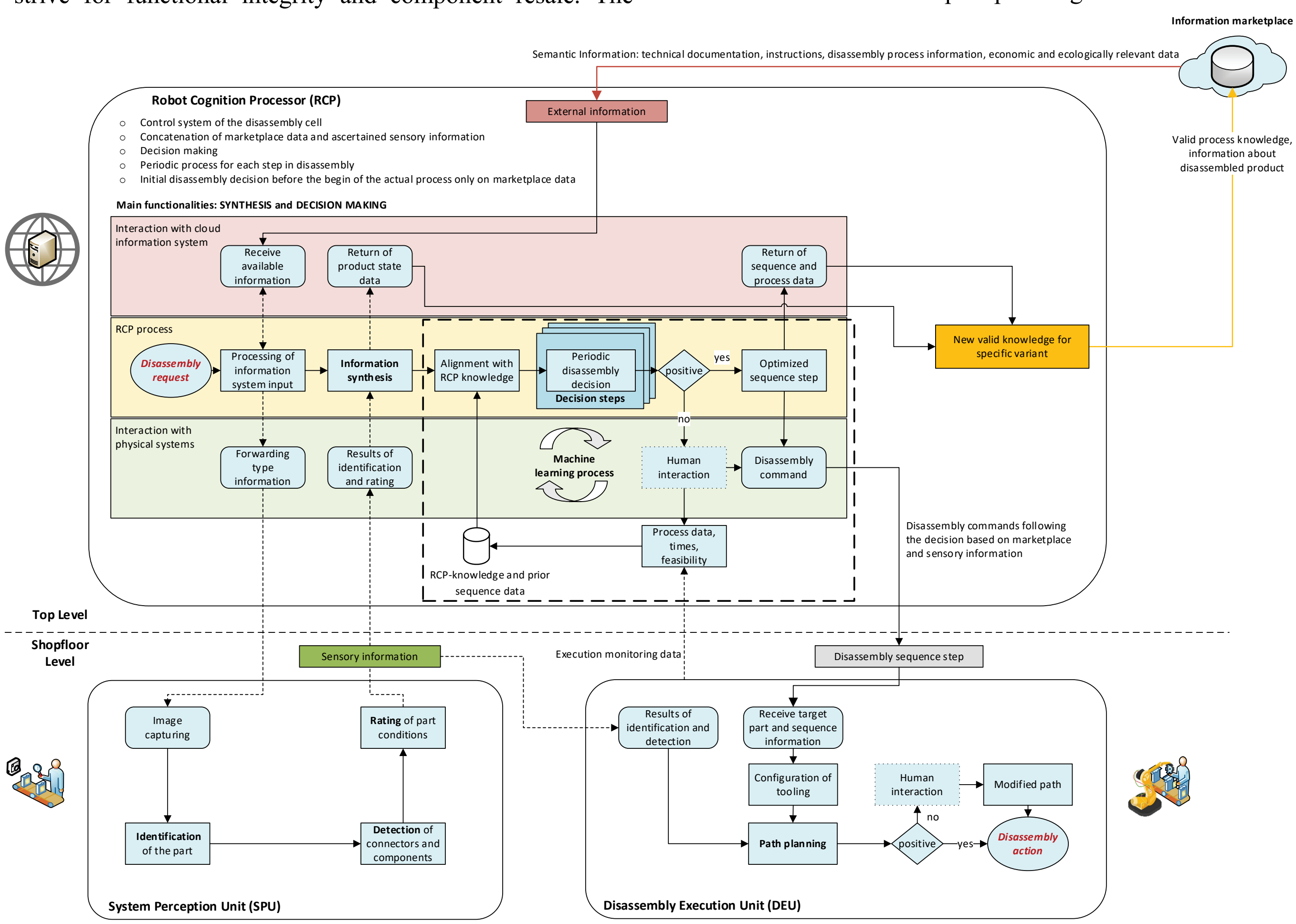

Figure 2. System concept of the agent-based disassembly system

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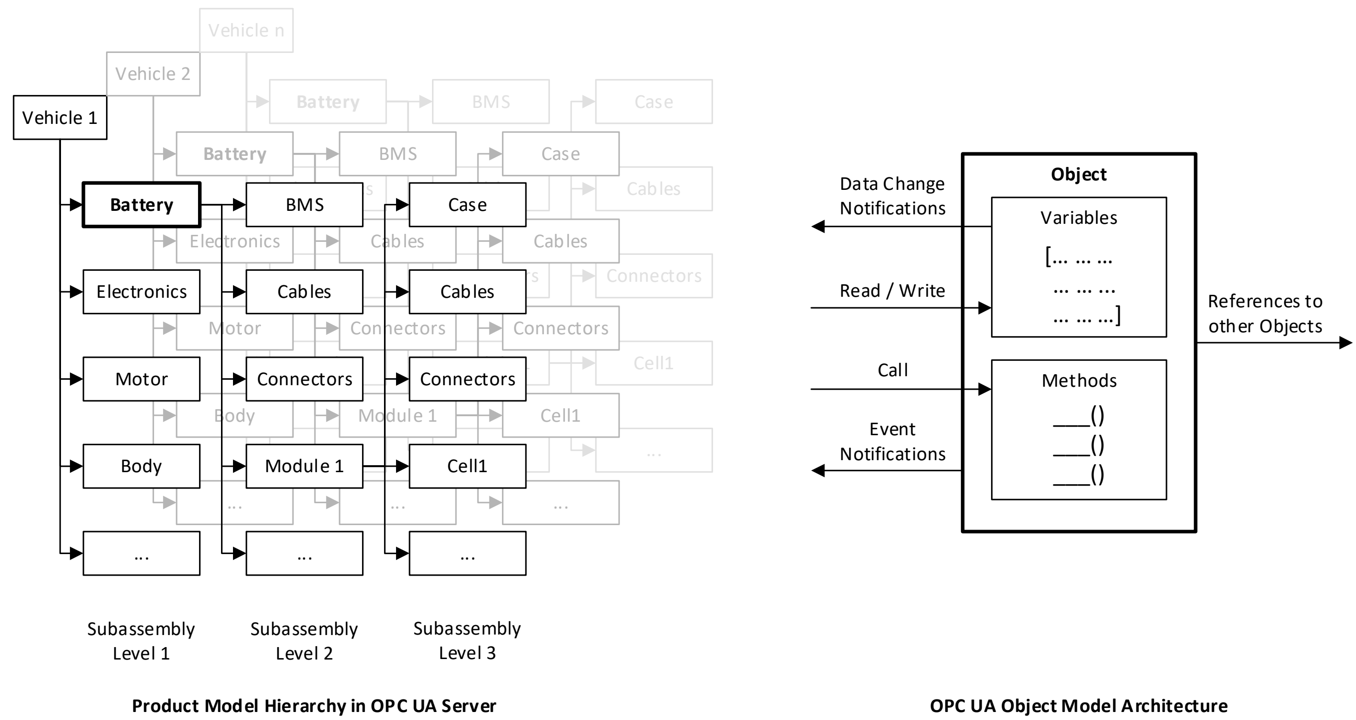

Figure 3. OPC UA product model hierarchy and object architecture

Sequence and process data is transferred back to the information marketplace for possible utilization in future disassembly targets of the same type or in other locations respectively other disassembly facilities connected to the *Recycling 4.0* framework.

In order to achieve the functionality as described, there are several preliminaries which have to be met:

- Accessible data structure for each hierarchy level of the target product
- Standardized data format to ensure cross-system interoperability
- Sufficient amount of training data based on real decisions of current processes for initial training

One elementary idea of the system is to use data processing capacities most efficiently at the information sources and sinks (edge computing principle). Bottlenecks in data transfer can be avoided that way and the available capacity is solely used for useful and requested information transfer. All agents in this configuration are independent parts of the system which can act inherently autonomously.

In order to align the dynamic data of the SPU to the model data from the information marketplace, a common framework of the digital model is required for interoperability. As a solution to this problem, the platform-independent interface OPC Unified Architecture (OPC UA) was selected in the project *Recycling 4.0*. The communication between the stakeholders can either take place as publisher/subscriber or client/server model [12]. The structure of the OPC UA model allows the alignment of external and sensory data in a single attributed dataframe per object node of each hierarchy level (see Fig. 3). Communication and data transfer in the OPC UA framework rely on the quality of the digital model deposited. In *Recycling 4.0*, the example of an electric vehicle battery was chosen. The structure of the car, the battery system and all relevant sub-assemblies, components and connectors are therefore modelled on the OPC server. Each object is represented by a node in the hierarchy tree.

The cognition module uses the available data for AI-enforced decision making. Decisions considering advanced circular economy models are too complex and dynamic for standard classification algorithms (such as decision trees or linear regression models). Up to the present, such connected information systems as described above do not exist in practice, therefore research cannot deliver the mechanisms and rules those systems would follow. However, Neural Networks (NN) as universal function approximators [13] deliver valuable output in dynamic and highly complex systems, being able to deal with manifold relations in wide, non-linear feature-maps. The approach presented in this paper is based on generic battery data of three different battery types (small BEV, mid-range BEV and PHEV). The composition of material rates and weight was defined according to [14]. The features used for classification in the RCP can be found in Table 1.

TABLE I. TABLE OF INPUT FEATURES

Feature	Symbol	Description
Type	Pr_V	Component type assigned to node (0=functional part, 1=connector, 2=case part, 3=wire, 4=board)
Hazmat	Pr_{Hz}	Containing hazardous materials, Boolean
ProductionDate	T_{Prod}	Date of Production

functionalIntegrity	Pr_{FI}	Potential operability / direct reuse possible, Boolean
PriceCore	C_{Core}	Purchasing price of the target core
CondDiagSOH	Pr_{SOH}	Diagnosed condition by state-of-health (SoH)
CondOpt	Pr_{Opt}	Optical diagnosis value after first step of disassembly
NodeIDASSEMBLY	Pr_{ID}	Individual node ID of the digital model
TDISASSEMBLY	T_{Diss}	Time for disassembly to next hierarchy level
PDISASSEMBLY	C_{Diss}	Specific cost of disassembly (hourly rates plus overhead surcharge)
ExpCompResale	I_{ComRes}	Expected profit from component resale
Demand	D_{Cmp}	Market demand indicator measured by time between last two orders of component
GradientPrice	∇_{Price}	Gradient of core price development from historical data
SocialAssessment	A_{Soc}	Social assessment factor of disassembly operation
EnvironmentalAssessment	A_{Env}	Environmental assessment factor of disassembly operation
WeightTHEORETICAL	Pr_{Wt}	Product weight according to technical documentation
WeightACTUAL	Pr_{Wa}	Actual product weight
MassConstituent (multiple)	$M_{Constituent}$	Material constituent shares
PriceConstituent (multiple)	$C_{Constituent}$	Material prices on a daily basis (given for each constituent)

In order to process the data for decision making in a NN, vectorization of the relevant datasets is required as input format. In pursuance of a highly concentrated information-set, a multistage pre-processing of the obtained node-data is performed in advance. In a first step, the material concentration and material price information can be condensed into a single value (I_{MatRec}), as both feature sets are only of relevance to a decision towards material recycling.

$$I_{MatRec}=\sum_{i=0}^{n_{Constituent}} Pr_{Wa} * M_{Constituent_i} * C_{Constituent_i} \tag{1}$$

The expected value of material-focused recycling is higher for a more advanced level of disassembly (L_{Diss}), as the achievable standard of purity can be increased by the removal of less important fractions, such as case components made of plastics or aluminium. Therefore, a factor is assigned to the expected material value considered to be recoverable, dependent on the disassembly grade.

$$I_{MatRec}(L_{Diss})=I_{MatRec} * \frac{e^{\frac{L_{Diss}}{L_{max}}}}{e} \tag{2}$$

The disassembly grade is determined by the initial node of the target object's structure at the point of disassembly request in respect to the maximum achievable level of disassembly (L_{max}). The factor delivers values between 36.7% and 100% of I_{MatRec} as an approximation to a realistic expectable return. Technologically achievable recycling rates of downstream processes are not taken into account at this point.

In the case of a decision for option 2, no further disassembly, the remaining components can be transferred to an established recycling process, such as the *JX* [15], *Umicore* or *LithoRec* battery recycling processes [16] for battery modules or other established material recovery processes for the remaining parts, such as case components, fasteners or electronics.

This first stage of pre-processing has reduced the number of input features per battery from 43 to 17.

The second stage of pre-processing reduces the number of input features by all features which are steady for all variants of the considered hierarchy level, such as hazmat factor and type in the case of the entire battery level. The node ID as structural model information is also removed, as it has no direct contribution to the disassembly decision. Moreover, features containing only redundant information are also excluded (e.g., T_{Diss}, as its information is already contained in the specific C_{Diss}). This step further simplifies the final processing by extracting irrelevant noise from the data affected. Finally, 13 features will be the input for the classification task.

A third and last step of pre-processing is the normalization of data.

$$\text{Feature}_{\text{Normalized}} = \frac{Feature\text{-}Feature_{min}}{Feature_{max}\text{-}Feature_{min}} \tag{3}$$

By normalization, the feature data is concentrated in a value range between 0 and 1, making the assessment of weights to each feature more balanced, as strong differences between value domains can be avoided.

On core disassembly level (entire battery), the decision has to be made before the actual disassembly process begins in order to avoid economic loss due to counterfactual process intake. Two modifications have to be made to apply the generalized cognition processor in this first step:

- The optical diagnosis factor cannot be applied as it has not yet been assessed for the target core concerned.
- The output category options zero and one both determine the target to be disassembled. The process is therefore pseudo-binary, as there is no difference to the first step in the process between the two categories. This modification is important for assessment of a validation data set as described in the final evaluation section.

For the evaluation of the first decision making approach of the RCP in this paper, the entire car is defined as the intake core eligible for a feasible disassembly. The decision making step in focus of this work is the disassembly decision on the level of the integral battery, which is investigated as a compliant three-class-classification problem. For the processing of the classification task, we consider a NN composed as a deep multilayer-perceptron. The network consists of six hidden layers, including two dropout-layers after the first and the second hidden layer (Fig. 4).

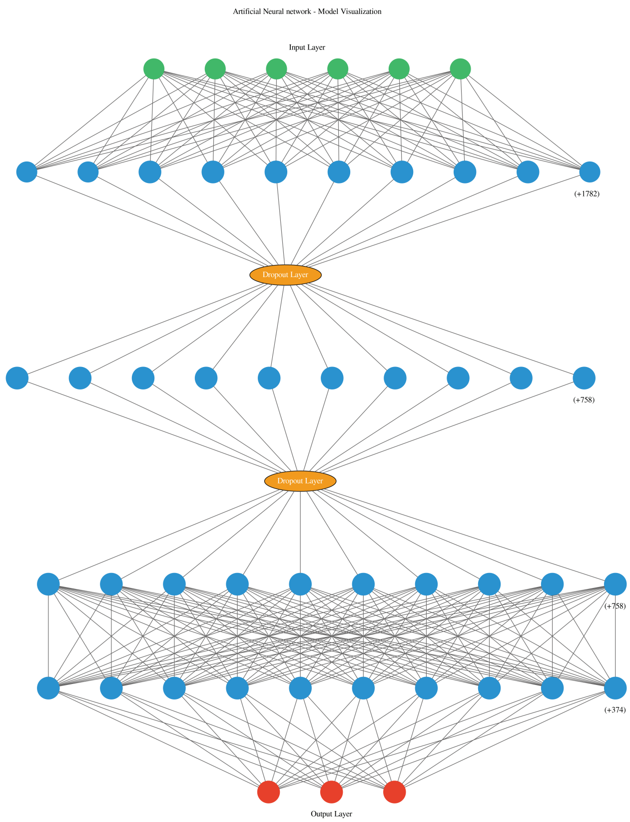

Figure 4. Schematic architecture of the Neural Network

The type of layers is "dense", as the network is fully connected. Apart from the output layer, whose activation function is "softmax" for classification purposes, the activation of the other layers is a rectified linear unit for better training behaviour [17]. The dropout rates are 0.2 for the first and 0.1 for the second dropout layer. As the Keras-API [18] is used for realization, the kernel initializer for initial weights is set to a randomized Gaussian with a standard deviation of 1.5. The model is compiled with Stochastic Gradient Descent (SGD) optimizer and categorical cross entropy as loss-function. The SGD optimizer is parameterized with a learning rate of 0.00015, a momentum of 0.3 and Nesterov accelerated in order to prevent early overfitting. All the hyperparameters were optimized following the general principles as described in [18] and [19] and fine-tuning the values manually in a narrow range around the given recommendations.

The model described is adaptable to new data, as the training of the model can be continued with each new sample available in the database for each level of disassembly hierarchy. Furthermore, each part that passes the process will deliver new aspects for improved training results even with constant architecture and hyper-parameters. In this way, the RCP is able to evolve in dynamic and constantly changing conditions of a global advanced circular economy.

IV. EVALUATION

Based on the generic battery data from literature [14], 600 individual generic battery cores with random values in given ranges for each of the relevant features according to Table 1 were generated for training and validation. The supervised training on pre-classified data is performed with weighted categories according to the amount and deviation of the regarded classes in the available samplings. As displayed in Fig. 5, the correlation magnitude between the features apart from correlation in price related features is relatively low. The strongest impact on the pre-classified training set has the battery's state of health (SoH) and the expected component resale value. The fact of a widely minor to none correlation in a linear model assures the proposal of a non-linearly activated multilayer-perceptron for the classification task. However, the analysed pre-classified training set only provides the starting input for the NN, as the main adaption phase would begin with the implementation in real processes.

The training process itself is performed as a k-fold cross validation (k=9) [20] after an initial holdout of 10% of the samples for a final double-check. Each training cycle runs over 120 epochs with 490 samples for training and 60 samples for validation. To prevent bias, the two datasets were separated in advance randomly by the time of loading the dataframes. The batch size is 8 and the samples are shuffled each time in advance. For each of the k-fold iterations, the output for training loss and accuracy as well as for validation loss and accuracy are documented (Fig. 6). In most cases, the validation accuracy reaches its best value after approximately 60 epochs, albeit in a few runs, the validation accuracy starts converging to its maximum value only at the end of the training. Furthermore, considering also the loss functions, it is shown that a gradual overfitting only intensifies after a high number of epochs, especially if the general level of convergence was notably higher than in other runs. As a result, an accuracy of **77.96%** with a standard deviation of 3.91% could be achieved for a correct classification in the validation data. A prediction for the isolated holdout dataset could confirm this result with an accuracy of 76.67%. The baseline of the classifier's accuracy considered is 33.34% (3 options).

A closer look at the prediction matrices shows that most failures in classification occur due to a wrong decision between option 0, disassembly for part recovery, and option 1, disassembly for improved recycling. Considering that, the physical output of the disassembly process regarding the level

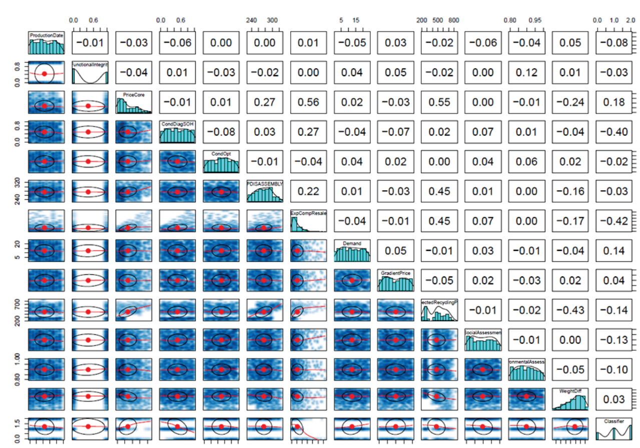

Figure 5. Correlation matrix of input features in training data

of disassembly determined by the decision processor would clearly have a higher success rate, as this physical process only has a binary option (whether to disassemble or not).

In conclusion, the evaluation of the training and validation sets shows that the network considered is capable of contributing to the determination of the product's disassembly grade with multiple EoL options by its ability to classify. The amount of data provided in this work can only be an initial input for the advanced disassembly system. In order to improve its decision quality in future operation phases, more data from real applications is required for the system to adapt to the dynamic and highly complex structure of the disassembly task. In operation, human decision should always be able to override the output of the system. These particular corrections are of great importance as they add valuable process knowledge to the future abilities of the RCP.

V. CONCLUSION

Disassembly is a key element of every complex products' recycling process. However, market principles of the reverse supply chain cannot be estimated holistically in advance, therefore a high level of adaptability is needed. Digitalization tools and advanced robotic systems can augment these processes as long as the necessary amount of information is provided. The integration of a cloud information system and a robot cognition processor enables the herein presented system to adaptively react to dynamic changes of the process environment by generalizing knowledge, both regarding the product as well as the process itself. Furthermore, the system actively contributes to the product knowledge by visual assessment and rating of individual parts.

Interoperability is also a key feature in the depicted structure, as the exchange of knowledge and information demands specific requirements for systems containing several, diverse types of agents. The use of an OPC UA framework for semantic interoperability also enables the transfer of concrete commands and sequence data of the robot in a standardized model back to the OPC server, enabling different stakeholders to exercise the acquired process knowledge on individual hardware. The authors developed an agent-based system, which is capable of integrating the disassembly operation into a holistic information flow management system. The available information can be utilized to predict and decide feasible levels of disassembly reliably and thereby increase the overall recycling process's efficiency. In-line, feature-based decision making by a machine-learning approach facilitates an adaptive EoL ecosystem at a critical point of the entire reverse supply chain.

The actual disassembly sequence is determined by the product's structure in the OPC model as well as the step-wise decision process of the RCP. Moreover, the classification of an assembly group or component strongly correlates with its position within the OPC structure, therefore these relational sequences have to be included in future approaches. Integrating sequential forecasting for individual features in order to predict future values can be considered by using recurrent networks, although the general economic system dynamics has to be taken into account. However, sequences and possible connections can become extraordinarily wide,

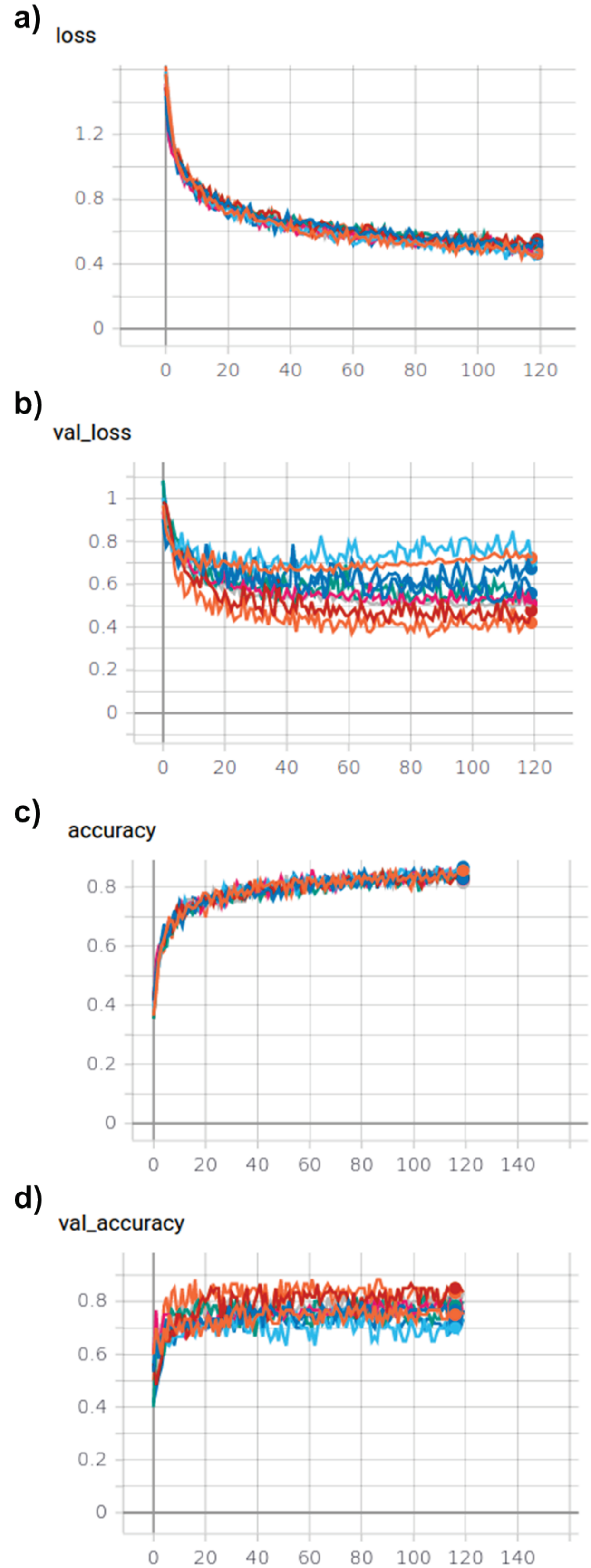

Figure 5. a) loss-function b) validation loss-function c) accuracy d) validation accuracy, all for k=9 on 120 training epochs

depending on the level of detail of the product and relevant data per component included. The integration and communication between the control architecture and the perception agent, especially regarding its rating capabilities as a system-immanent source of relevant information for the classification process as well as an optimization of the feature intake based on the experiences in the full-scale reverse supply chain model are subject to future research of this project. Moreover, the case of false-positive classification would in this concept lead to a disassembly at a potential loss for the disassembler. To overcome this, an optimization of the classification rate is necessary as a future improvement to the proposed architecture.

The benefits of the presented system for disassembly and therefore the circular economy process lie in the faster and more exact decisions based on predicted features available through the marketplace infrastructure. This enables the *Recycling 4.0* ecosystem to contribute to EoL processing feasibility no matter what the final option, as all system participants profit from the available information being processed into actual knowledge.

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REFERENCES

[1] Resolution adopted by the General Assembly on 25 September 2015: A/RES/70/1, 2015. Accessed: Apr. 15 2019. [Online]. Available from: https://www.un.org/ga/search/view doc.asp?symbol=A/RES/70/1&Lang=E

[2] G. Seliger, “Assembly and Disassembly,” in Handbook of Mechanical Engineering, H. Dubbel, K.-H. Grote, and J. Feldhusen, Eds., 23rd ed., Berlin, Heidelberg: Springer-Verlag Berlin Heidelberg, pp. 97-103, 2011.

[3] H. Levesque and G. Lakemeyer, “Chapter 23 Cognitive Robotics,” in Foundations of Artificial Intelligence, Handbook of knowledge representation, F. van Harmelen, V. Lifschitz, and B. Porter, Eds., 1st ed., Amsterdam, Boston: Elsevier, pp. 869–886, 2008.

[4] C. Knieke, S. Lawrenz, M. Fröhling, D. Goldmann, and A. Rausch, “Predictive and Flexible Circular Economy Approaches for Highly Integrated Products and their Materials as Given in E-Mobility and ICT,” MSF, vol. 959, pp. 22–31, 2019, doi: 10.4028/www.scientific.net/MSF.959.22.

[5] J. Jungbluth, W. Gerke, and P. Plapper, “An Intelligent Agent-Controlled and Robot-Based Disassembly Assistant,” IOP Conf. Ser.: Mater. Sci. Eng., vol. 235, no. 1, p. 12005, 2017, doi: 10.1088/1757-899X/235/1/012005.

[6] S. Vongbunyong and W. H. Chen, Disassembly Automation. Cham: Springer International Publishing, 2015.

[7] H. Poschmann, H. Brüggemann, and D. Goldmann, “Robotized Disassembly as an Essential Driver for Digitalization in Future Recycling Processes,” in Recycling und Rohstoffe, vol. 13, E. Thomé-Kozmiensky, O. Holm, B. Friedrich, and D. Goldmann, Eds., Nietwerder: Thomé-Kozmiensky Verlag GmbH, pp. 570–587, 2020.

[8] Y. Feng, Y. Gao, G. Tian, Z. Li, H. Hu, H. Zheng, “Flexible Process Planning and End-of-Life Decision-Making for Product Recovery Optimization Based on Hybrid Disassembly”, IEEE Trans. Automat. Sci. Eng., vol. 16, no. 1, pp. 311-326, 2019, doi: 10.1109/TASE.2018.2840348.

[9] J. Li, M. Barwood, S. Rahimifard, “A multi-criteria assessment of robotic disassembly to support recycling and recovery”, Resources, Conservation and Recycling (Elsevier), no. 140, pp. 158-165, 2019, doi: 10.1016/j.resconrec.2018.09.019.

[10] G. Tian, M. Zhou, P. Li, “Disassembly Sequence Planning Considering Fuzzy Component Quality and Varying Operational Cost”, IEEE Trans. Automat. Sci. Eng., vol. 15, no. 2, pp. 748-760, 2018, doi: 10.1109/TASE.2017.2690802.

[11] H. Poschmann, H. Brüggemann, and D. Goldmann, “Disassembly 4.0: A Review on Using Robotics in Disassembly Tasks as a Way of Automation,” Chemie Ingenieur Technik, vol. 92, no. 4, 2020, doi: 10.1002/cite.201900107.

[12] OPC Foundation, “OPC Unified Architecture. Part 1 : Overview and Concepts: Release 1.04,” Accessed: Feb. 09 2020. [Online]. Available from: https://opcfoundation.org/developer-tools/specifications-unified-architecture/part-1-overview-and-concepts/

[13] K. Hornik, M. Stinchcombe, and H. White, “Multilayer feedforward networks are universal approximators,” Neural Networks, vol. 2, no. 5, pp. 359–366, 1989, doi: 10.1016/0893-6080(89)90020-8.

[14] J. Diekmann et al., “Ecological Recycling of Lithium-Ion Batteries from Electric Vehicles with Focus on Mechanical Processes,” J. Electrochem. Soc., vol. 164, no. 1, A6184-A6191, 2017, doi: 10.1149/2.0271701jes.

[15] Y. Haga, K. Saito, and K. Hatano, “Waste Lithium-Ion Battery Recycling in JX Nippon Mining & Metals Corporation,” in The Minerals, Metals & Materials Series, Materials Processing Fundamentals 2018, G. Lambotte, J. Lee, A. Allanore, and S. Wagstaff, Eds., Cham: Springer International Publishing, pp. 143–147, 2018.

[16] T. Elwert et al., “Current Developments and Challenges in the Recycling of Key Components of (Hybrid) Electric Vehicles,” Recycling, vol. 1, no. 1, pp. 25–60, 2016, doi: 10.3390/recycling1010025.

[17] X. Glorot, A. Bordes, and Y. Bengio, “Deep Sparse Rectifier Neural Networks,” Proceedings of the Fourteenth International Conference on Artificial Intelligence and Statistics, no. 15, pp. 315–323, 2011. Accessed: Apr. 2 2020. [Online]. Available from:http://proceedings.mlr.press/v15/glorot11a/glorot11a.pdf

[18] F. Chollet, Deep learning with Python. Shelter Island, NY: Manning Publications Co, 2018.

[19] A. V. Joshi, Machine Learning and Artificial Intelligence. Cham: Springer International Publishing, 2020.

[20] R. Kohavi, “A study of cross-validation and bootstrap for accuracy estimation and model selection,” IJCAI'95: Proceedings of the 14th International Joint Conference on Artificial intelligence, no. 2, pp. 1137–1143, 1995. Accessed: Feb. 3 2019. [Online]. Available from: https://dl.acm.org/doi/10.5555/1643031.1643047

