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# Self-learning assembly systems during ramp-up

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**Abstract**. Achieving the targeted production volume during the ramp-up phase plays an important role for the economic success of manufacturing companies. But ramp-up phases are usually characterized by a high degree of uncertainty, as many situations arise for the first time. These unexpected events lead to errors and faults in automated processes which cause losses in the overall production volume. This paper proposes an architecture for assembly systems to predict and avoid faults of the assembly process during ramp-up through self-learning. Different algorithms for self-learning components are evaluated. By using real production data sets, neural networks could be identified as the best solution.

## 1 Introduction

Due to continuously shortening product lifecycles, the cost and duration of the production ramp-up phase are becoming increasingly important for the economic success of a manufacturing company [1]. Shorter product lifecycles reduce the time available for amortisation of required investments and the costs for development. Lost profits are in addition a result of any delay in the achievement of the targeted production volume. Faster and more robust ramp-ups are therefore needed [2]. The ramp-up phase is thereby defined as the period of time between the end of development and the achievement of full capacity utilisation of the production system [3]. In the ramp-up phase, many situations arise for the first time and the system behaviour underlies a high degree of uncertainty [4]. Particularly in automation this can cause interruptions of the ramp-up and make adoptions of the system necessary [5]. The performance of a production ramp-up can be evaluated by the “magic triangle” consisting of quality, time and cost [6]. Fleischer [7] has shown that the goals in quality seem to be most important and that the produced quality has a direct impact on the other two dimensions. This means that the ramp-up targets concerning time and cost can be described as a function depending on the achieved quality. As a result, the overall ramp-up can only be successful if the targeted production quality can be achieved quickly and steadily. Several studies have proven that less than 44% of the evaluated production ramp-ups have successfully achieved their given ramp-up targets [8, 9]. A possible explanation for this is given by Wiendahl [10] in the exposure of the production system to internal and external disturbance

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factors, which cannot be avoided or controlled. As a result, self-learning production systems need to be developed that can easily adapt to the unknown disturbance factors within the ramp-up phase, avoid potential faults and assure a quick and steady achievement of the targeted production quality. In this paper, we propose a possible architecture for self-learning assembly systems, which improves and stabilizes assembly quality and thereby speeds up ramp-ups using findings in the field of machine learning. Afterwards, different implementations of the fault-predicting self-learning component are evaluated and compared with respect to their performance in an existing real-world scenario.

### 1.1 Description of the real-world assembly scenario

In the automotive industry, most of the manufacturing processes are already highly automated [11]. Nevertheless, particularly the automotive assembly has remained an area still dominated by manual labour, offering a high potential for automation [12]. Recent developments in robotics have revealed a new and sensitive generation of robots [13]. Their sensitive capabilities allow for deployment within a wider range of assembly tasks [14], which will lead to a significant increase of automation in the automotive assembly in the future [13], making robust and fast ramp-ups of automated assembly processes even more important. In the chosen scenario a sensitive robot is used for the assembly of rubber plugs, a part that is needed for sound and moisture insulation and that requires a force controlled assembly process. The resulting assembly quality can take two states: “OK” if the plug is fully and correctly fitted, or “not-OK” if the plug is not or only partially fitted. Figure 1 shows the distribution of unsuccessful (not-OK) plug assemblies over time when the technology was first introduced into a real production line in 2016. The absolute number of plugs to be assembled every day was kept constant over time at 15.000 a day.

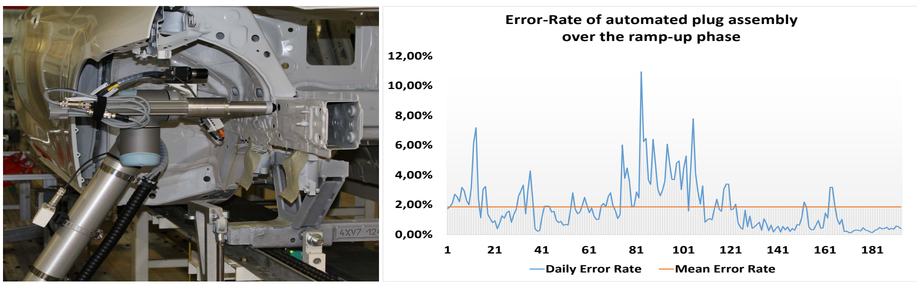


Fig. 1: Error rate of plug assembly throughout the first ramp-up.

It can be observed that between day 81 and day 110 of the ramp-up the quality of the assembly process decreased, without any changes made to the internal parameters. Several external disturbance factors that could not be avoided for the developed plug-assembly process were identified by expert interviews, such as changes in the environmental temperature, changes in the hardness of the plug over its temperature and different production batches, mechanical tolerances and others.

## 2 Proposed architecture of self -learning assembly systems

The architecture proposed follows the intuition of deviating from a given assembly policy only in the likelihood of an unsuccessful assembly. It will take proactive countermeasures whenever the first self-learning component predicts an unsuccessful assembly, based on changes of the monitored external parameters, with a certain high probability. Therefore, the system requires the following characteristics: awareness, prediction, decision-making and learning. The proposed strategy aims at imitating a practical human approach in industrial practise instead of continuously optimizing the process parameters. This allows for better illustration of the decision process to human operators compared to a mere black box approach, thereby enhancing process understanding.

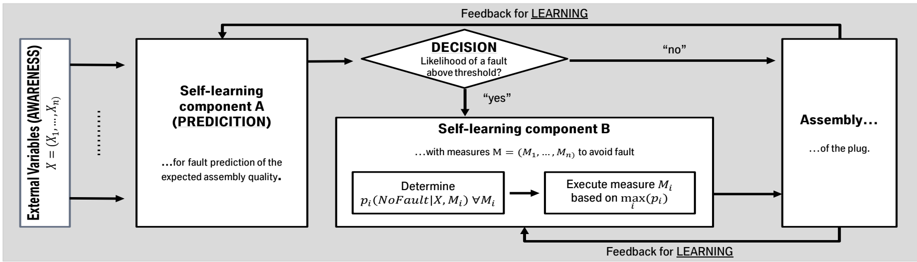


Fig. 2: Architecture of self-improving assembly systems.

Figure 2 shows the architecture of the system. By means of a second self-learning component, the system chooses out of a set of given countermeasures, the one that is most likely to prevent the expected unsuccessful assembly. The implementation of a frequent feedback of the assembly result will allow for self-learning and self-improvement in the performance of the assembly system over time.

Using the architecture's separability, we evaluate potential algorithms for the fault predicting component. Fault prediction has often been addressed as a classification problem in past research, being given its similarity to fault detection [15]. Gertler [16] distinguishes between model-based and model-free methods for fault detection systems: Model-based methods compare actual sensor data with computations from mathematical plant models. Thereby imposed requirements towards high plant modelling accuracy can hardly be met in ramp-up phases, since novel automated assembly processes are characterized by complexity and uncertainty. Model-free methods do not require a mathematical plant model; generally, they are not restricted by explicitly modelled a-priori knowledge [17]. In this setting, data-driven methods, as a subset of model-free methods are of interest as required process-related causalities can often be extracted from process data [18]. For the fault predicting component, support vector machines (SVM) and artificial neural networks (ANN), in particular multi-layer perceptron (MLP) and learning vector quantization (LVQ) have been identified as suitable learning models as justified in the following: MLPs are widely used for various classification problems. Their advantages include scalability and capability to classify non-linearly separable data to very high accuracy and sequential learning; yet,

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performance strongly depends on the quality and quantity of data, the architecture (layers, activation function) and the training procedure [19]. LVQ is a nonlinear classifier with a competitive layer to directly classify the input into subclasses while a subsequent linear layer classifies into the target classes [20]. Advantages include the representation of interpretable prototypes, adjustability of model complexity, ease of implementation, less required computation power, and the capability for active learning [21, 22]. Generalized Learning Vector Quantization (GLVQ) extends the concept of LVQ by minimizing a cost function of error $E$ on an set of input vectors $v \in V$ and prototypes $w \in W$ with a classifier function $\mu_d^W$ and transfer function $f$,

$$E = \frac{1}{2} \sum_{v \in V} f(\mu_d^W(v)) \text{ with } \mu_d^W(v) = \frac{d^+(v) - d^-(v)}{d^+(v) + d^-(v)} \text{ and often sigmoid } f, \quad (1)$$

with $d^+(v) = d(v, w^+)$ and $d^-(v) = d(v, w^-)$, the dissimilarity (e.g. euclidean metric) between $w^+$, the most similar prototype within the class and the input $v$ and respectively $w^-$, the most similar prototype of other classes. GLVQ is a maximum hypothesis margin classifier, in contrast, SVM is a maximum separation margin classifier [22]. The soft-margin SVM is a popular decision model that usually is defined by

$$\min \left( C \sum_{n=1}^{N} \xi_n + \frac{1}{2} \|w\|^2 \right) \text{ s.t. } y_i(w \cdot x_i + b) \geq 1 - \xi_n \quad (2)$$

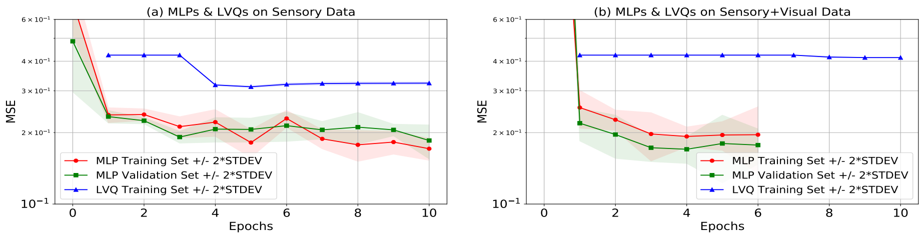
whereas $\xi_n$ penalizes misclassified points and $C$ balances between margin and penalty. SVMs exhibit good robustness, sparsity, generally low computational complexity, good generalization behaviour with a small number of samples; furthermore, sufficient choice of a kernel function enables fitting non-linearly separable data, and incremental learning SVM methods are available [23, 24].

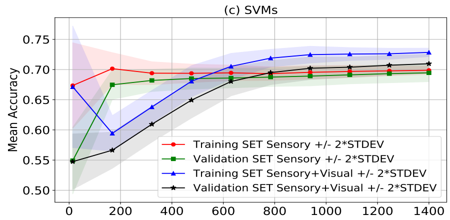
## 3 Evaluation

To train and evaluate the capabilities of the identified self-learning algorithms for fault prediction we used a real production data set consisting of 2000 samples[1], which was splitted (70:30) in a training and validation set . Each sample consists of sensory (plug hardness, plug temperature, hole type, room temperature, humidity, luminosity) and visual data (360X360 pixel picture of the plug in pre-assembly position), covering the external parameters which were identified by experts. Using the best achieved parameter set for each algorithm, we compared the prediction accuracy of the identified algorithms. Figure 3 shows that for all algorithms a best result was derived. While both evaluated MLPs contain two hidden fully-connected RELU layers[2], we additionally used three convolution layers[3] to preprocess data when working with visual input. Training, using an Adam optimizer, was stopped if the validation error increased in five successive epochs, weights were saved at last decreasing epoch. Among the two SVM classification types, a C-type[4] with an linear activation showed the best results. As the results of LVQ1 and GLVQ were very similar and both do not offer an

[1] "OK":"not OK" = 57:43 [2] 200 neurons wide [3] 32 filters, 5x5 kernel, max-pooling [4] C=10

promising alternative to SVMs and MLPs, they were generalized into one graph and details on implementation will be skipped. Evaluations shown in Table 1 were carried out after training, using the validation data set. The results show that MLPs performed best with an overall accuracy of 77%. The F2 score was identified best for evaluation, as the miss of a not-OK should be rated worse than a wrong prediction in the case of an OK. Figure 3 also shows that prototype based algorithms do not seem to operate well for this application. The applied nearest neighbour method leads to a high amount of wrongly predicted OKs, resulting in a very low sensitivity. This can be explained by the small amount of possible prototypes in the required case of a binary classification, which also leads to the observed decline in sensitivity when visual data is added. Neither NN nor SVM suffer from this problem and seem both to deliver good results.




(d) Table 1: Evaluation based on confusion matrix

| | Specificity | Sensitivity | PPV | NPV | Accuracy | F2 Score |
|---|---|---|---|---|---|---|
| MLP Sensory+Visual | 0.79 | 0.75 | 0.75 | 0.79 | 0.77 | 0.75 |
| MLP Sensory | 0.80 | 0.60 | 0.71 | 0.70 | 0.71 | 0.62 |
| LVQ1 Sensory+Visual | 0.99 | 0.01 | 0.60 | 0.55 | 0.50 | 0.01 |
| LVQ1 Sensory | 0.92 | 0.38 | 0.80 | 0.64 | 0.68 | 0.43 |
| GLVQ Sensory+Visual | 0.92 | 0.22 | 0.69 | 0.58 | 0.60 | 0.25 |
| GLVQ Sensory | 0.84 | 0.53 | 0.73 | 0.68 | 0.70 | 0.56 |
| SVM Sensory+Visual | 0.78 | 0.72 | 0.73 | 0.77 | 0.75 | 0.72 |
| SVM Sensory | 0.81 | 0.53 | 0.70 | 0.68 | 0.69 | 0.56 |

Fig. 3: Learning Curves and Evaluation Table of different self-learning algorithms

MLPs slightly outperform SVMs through their ability to better handle complex data with a lot of noise. SVMs achieve good results when data complexity and available data is low and might be a good solution in such a case.

## 4 Conclusion

In this paper, we presented an architecture for self-learning assembly systems during ramp-up. We were able to show that existing self-learning algorithms can successfully be implemented for fault prediction of an existing assembly system in the automotive industry. We could also illustrate that the application of model-free methods allow for a significant reduction of the rate of unexpected not-OK assemblies by achieving a prediction accuracy of 77%, allowing a significant improvement of assembly systems during ramp-up. In a next step, the second self-learning component for the evaluation and execution of countermeasures needs to be investigated. For the purpose of consistency in the system architecture MLPs could be applied again as they have proven to be a good solution, but also reinforcement learning appears to be a promising method and will be evaluated in future research.

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## References


[1] H. Winkler, M. Heins, P. Nyhuis, A controlling systems based on cause-effect relationships for the rampup of production systems, *Prod. Eng. Res. Devel.*, 1:103-111, Springer Verlag, 2007.

[2] W. Bauer, O. Ganschar, B. Pokorni, S. Schlund, Concept of a failures management assistance system for the reaction on unforeseeable events during the ramp-up, *Procedia CIRP 25*, pages 420-425, Elsevier, 2014.

[3] R. Bohn and C. Terwiesch, The economics of yield-driven processes, *Journal of Operations Management*, 18(1):41-59, Elsevier, 1999.

[4] I. Basse, S. Schmitt, T. Gartzen and R. Schmitt, Solution principles for managing instabilities in ramp-up, *Procedia CIRP 20*, pages 93-97, Elsevier, 2014.

[5] C. Brecher, S. Kozielski, L. Schapp, Integrative Produktionstechnik für Hochlohnländer. In C. Brecher, editor, *Integrative Produktionstechnik für Hochlohnländer*, pages 47-70, Springer Verlag, 2011.

[6] L. Surbier, G. Alpan, E. Blanco, A comparative study on production ramp-up: state-of-the-art and new challenges, *Production Planning & Control*, 25(15):1264-1286,Taylor and Francis, 2014.

[7] J. Fleischer, Proaktive Anlaufsteuerung entlang der Wertschöpfungskette von Produktionssystemen (ProactAS), *Schneller Produktionsanlauf in der Wertschöpfungskette*, pages 29-36, VDMA Verlag, 2007.

[8] F. Straube, D. Fitzek, Herausforderungen und Erfolgsfaktoren im Anlaufmanagement der Automobilindustrie, Jahrbuch der Logistik, 2005:44-47, Handelsblatt, 2005.

[9] H. Meier, M. Hormuth, Holistic ramp-up management in SME-networks, *Proceedings of the 39th international seminar on manufacturing systems*, pages 123-128, June 7-9, Ljubljana (Slovenia), 2006.

[10] H.-P. Wiendahl, M. Hegenscheidt, H. Winkler, Anlaufrobuste Produktionssysteme, Werkstattstechnik online, 92(11/12):650-655, 2002.

[11] J. Roscher, Bewertung von Flexibilitätsstrategien für die Endmontage in der Automobilindustrie, Universität Stuttgart, 2008.

[12] J. Werner, Methode zur roboterbasierten förderbandsynchronen Fliešmontage am Beispiel der Automobilindustrie, Utz, 2009.

[13] W. Huber, Industrie 4.0 in der Automobilproduktion, Springer Vieweg, 2016.

[14] D. Steegmüller, M. Zürn, Wandlungsfähige Produktionssysteme für den Automobilbau der Zukunft, Springer Vieweg, 2014.

[15] J. Yan, Machinery Prognostics and Prognosis Oriented Maintenance Management, Wiley, 2015.

[16] J. Gertler, Fault Detection and Diagnosis in Engineering Systems, CRC Press, 1998.

[17] E. Wandekoken, F. Varejao, R. Batista, Support Vector Machine Ensemble Based on Feature and Hyperparameter Variation for Real-World Machine Fault Diagnosis. In A. Gaspar-Cunha, R. Takahashi, G. Schaefer, L. Costa, editors, *Soft Computing in Industrial Applications*, pages 271-282, Springer Verlag, 2011.

[18] L. Chiang, E. Russell, R. Braatz, Fault Detection and Diagnosis in Industrial Systems, Springer, 2001.

[19] I. Goodfellow, Y. Bengio, A. Courville: Deep Learning, MIT Press, 2016.

[20] Management Asociation, Information Resources, Data Mining: Concepts, Methodologies, Tools and Applications, IGI Global, 2013.

[21] D. Nova, P. Estevez, A review of learning vector quantization classifiers, *Neural Computing and Applications*, 25, pages 511-524, Springer, 2014.

[22] T. Villmann, A. Bohnsack, M. Kaden, Can Learning Vector Quantization be an Alternative to SVM and Deep Learning? - Recent Trends and Advanced Variants of Learning Vector Quantization for Classification Learning, *Journal of Artificial Intelligence and Soft Computing Research*, 7(1), De Gruyter, 2017.

[23] C. Bishop, Pattern Recognition and Machine Learning, Springer, 2006.

[24] G. Cauwenberghs, T. Poggio, Incremental and decremental support vector machine learning, *Proceedings of the 13th International Conference on Neural Information Processing Systems*, pages 388-394, MIT Press, 2001.