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Online Condition Monitoring Tool for Automated Machinery

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Abstract

In order to increase machinery resource, energy and time efficiency, Condition Monitoring (CM) offers a wide set of beneficial tools. Those tools can basically be segmented in maintenance improvements or the optimization of process parameters. CM requires data input from a component, which is then analyzed using data based or physical models, which return an estimate of the component's current condition. The use of high quality sensors in a stable laboratory environment generally leads to an overemphasizing of the results which CM systems achieve in an industrial environment. Additionally, the installation of sensors is not always economically feasible for low-cost machinery. To overcome this, the CM system which is presented in this paper uses data, which is usually present in the PLC, as a consequence thereof, the data quality is significantly lower compared to dedicated sensor equipment. A real production machinery is further used to demonstrate the capabilities of condition monitoring in an industrial environment. The data driven CM process, which is used in this application example is compared to a model driven approach, conducted on a test equipment machine.

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Keywords: Monitoring and Diagnostics, Optimisation of Machining Processes, Numerical and Analytical Modeling

1. Introduction

In the last years, the pressure for a better and more sophisticated approach in maintenance led to the development of condition monitoring (CM) and predictive maintenance (PM) systems. Condition monitoring uses data which is present in the machine, to calculate a quantifiable condition of a component or a machine. This condition is a numeric expression of the health of a component, and can quantify faults which are modeled in the calculation algorithm resulting from wear, friction, heat dissipation and similar.

Using this condition value, the efficiency of the machine can be improved in several different ways. Approaches, such as predictive maintenance, can be used to reduce the amount of maintenance time on the machine. This approach allows to better plan any maintenance action, based on the condition of the component, rather than on afixed maintenance cycle. If the maintenance is based on the real condition, it also reduces the number of components, which are maintained, despite being perfectly healthy.

Using condition monitoring, the machine can also be improved in respect to its production and energy efficiency. Unhealthy and unreasonably damaging processes can be identified by following the condition of such processes. Also, energy inefficient processes can be identified, by identifying the energy consumption accordingly.

To make such a condition monitoring accessible to any type of machinery, this work focusses on sensors, which are already available in the machine. Components, such as frequency converters have a built-in current and voltage sensor, which can be used instead of an external sensor. This allows the installation of such a system even for cheap components, where a data acquisition via external sensors is too costly. The downside of this approach is a reduced data quality, compared to a high resolution external sensor.

2. Motivation

There are many different machine components available in any possible combination in industry. This paper focusses on a spindle drive, consisting of a servo motor, a gearbox, and a mechanical spindle. The spindle drive combines electrical, mechanical and thermal systems in one, making it one of the most complex systems in a standard machine. Thus, it is a good example for a generic component, which can be reused for simpler components.

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2.1. Related Work

There are many different approaches to spindle drive monitoring, which are presented by [1], which refers the reader to [2] and [3], or various parameter identification methods as presented by [4]. This work will focus on the approach presented by [1] and compare it to a data driven approach, which will be elaborated further.

In [5] a condition monitoring for an electrical motor is presented which solely relies on current measurements. The goal is to replace vibration measurements by currents measurements, delivering the same result. Because stator vibration measurement requires full access to the stator and rotor, this technique is usually too expensive for small scale equipment. The usual bearing failure can be measured consistently by a vibration sensor. The current measurements yielded similar frequency responses and offer a unique opportunity for a cheap bearing failure detection.

Similarly [6] presents an approach to measure the condition of an electrical motor using frequency analysis. The proposed algorithms is based on the fact, that any vibration due to a motor error is also transferred to the current signal, based on the electromechanical feedback through the motor windings. Using a simple analysis of the induced frequencies depending on a certain error case, an error can be identified using a frequency spectrum of the current feedback signal.

3. System Setup

The whole condition monitoring process, as presented in this work, is based on a software tool. As mentioned above, the absence of external sensors makes it necessary to use of internal sensors in the machine. Thus, the installation of such a system is a mere software update. This software update is based on three software layers. The first layer is the data acquisition layer, which is situated on the PLC itself. The second layer it the data interpretation loop, which conducts the condition calculation and prediction, the third layer it the broadcasting to the end user, which needs to interact with the data in a meaningful way.

3.1. Cyber-Physical Data Connection

The data acquisition, which runs on the PLC, works independently of the machine control. The data is handed to the data acquisition function, which buffers the sampled data, such that the condition monitoring software can load it asynchronously. First, the sensors value is loaded in the memory of the PLC and then placed into a predefined array. This process is repeated, until the array is full (at a fixed predefined size). If that occurs, the array is stored in an output buffer, and a flag is set that the data is ready to transfer. At this point, the data acquisition loop waits for the next trigger to start acquiring data again, which is set in the machine control, e.g. at the start of a crucial process which should be monitored. The data transfer loop waits until an external application sets the data transfer flag and accepts the transferred data to release the output buffer for the next data transfer. This asynchronous data transfer allows the data acquisition to continue, during the data transfer time. Most of the monitored processes take two or more seconds to run, which is more than enough time to transfer the data.

This data acquisition is built in such a way that it can be implemented as a software update to any structured text program, which makes it cheap to install on any machine. On the side of the condition monitoring algorithm, a virtual counterpart of the monitored component is created. Using object oriented programming languages, the monitored component can be treated as individual cyber object, which represents the physical component in an abstract way. Each cyber-physical instance, as this construct is called, has several physical properties and functions related to it, as depicted in Figure 1. Each component has a data handler, which is continuously waiting for data from the data acquisition loop, as soon as the data ready flag is set in the PLC, the condition monitoring algorithm loads the data in its memory and starts the predefined algorithm. For each data set which is transferred this way, a new condition value is calculated.

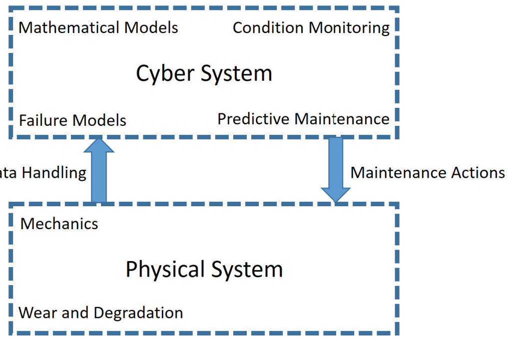

Fig. 1. Cyber-physical Instance

3.1.1. Data Interpretation

After the data is transferred to the condition monitoring application, the interpretation algorithm is run. This algorithm includes all models specified by the user, which lead to the calculation of the condition, prediction and any other useful information. This can include a detailed energy consumption analysis, or data, which is critical to the production development.

This work focuses on the calculation of the condition and the prediction algorithm. To calculate the condition of the component, two approaches are introduced, based on the work presented by [1]. The two approaches are a model-based approach, which identifies the physical model parameters of a dynamic differential equation system. The second approach focusses on a statistical approach, based on control charts, as presented by [7].

3.1.2. Model-based approach

The model-based approach focusses on the dynamic model of the corresponding component. In this case, the model of a electrical spindle drive is introduced.

The electrical model, as presented by [8] is shown in (1) and (2).

$$L_s I_d(t) = U_{sd} - RI_d + pL_s\omega_m I_q \tag{1}$$

$$L_s I_q(t) = U_{sq} - RI_q - pL_s\omega_m I_d - \tfrac{3}{2}p\omega_m\Psi_0 \quad (2)$$

The model of the connected spindle mechanics looks as follows:

$$\Theta_{tot}\omega_m(t) = \tfrac{3}{2}p\Psi_0 I_q - \mu_s \mathrm{sign}(\omega_m(t)) - \mu_v\omega_m(t) - F_p\tfrac{n10^{-3}}{2\pi\gamma} \quad (3)$$

With the following parameters:

L_s: Inductance of the windings.

R: Resistance of the windings.

Ψ_0: Motor Constant.

p: Number of pole pairs.

U_{sd}, U_{sq}: Control action voltages.

I_q: Acting current.

I_d: Blind current.

ω_m: Velocity of motor shaft.

γ: Gearbox transmission ratio.

n: Spindle increment

Θ_{tot}: Total inertia.

F_p: Process force.

μ_s, μ_v: Friction parameters

Using this model, it is possible to conduct a parameter identification process. Using a special trajectory, as presented by [1], the parameters can be identified during the operation of the machine, which is favorable due to production efficiency. An online parameter test allows following the parameters in real time. The identified parameters are:

Ψ_0: Motor Constant

μ_s, μ_v: Friction parameters

Θ_{tot}: Total inertia.

These four parameters offer critical insight into the behaviour of the electrical spindle. The friction parameters give a good response on the condition of the mechanical part (gearbox, spindle, bearings and guidance). On the other hand, the motor constant can yield possible interpretations on the health of the electrical motor. The total inertia gives a good feedback on any manual change to the system, which is not unusual for this kind of machinery. As any change can have influences on the monitoring algorithm, it needs to be monitored in detail.

These four parameters can be considered during a parameter identification approach to calculate the condition of the spindle. To have a uniform condition interpretation across different physical parameters, the same statistical process as for the data-based approach is used. The proposed statistical algorithm takes the raw data from trajectories and recalculates a condition value between 0 and 100. The same can be done using the physical parameters presented above.

As such, a normalisation of all results is achieved, and a comparable basis is created. For example, a temperature condition of 65 (e.g. overheating) can be compared to a condition of 54 which is related to the friction parameter. Using absolute values between 0 and 100 a interaction with the machine personell is much easier, because no physical understanding of the process is needed.

3.1.3. Data-based approach

The data-based approach is of statistical nature. Instead of using physical models of the components, the individual data set and trajectory of each production cycle is monitored. Without any connection to a physical model, critical points in the trajectory are chosen, which are to be monitored by the system. Figure 2 shows a typical trajectory of a joining process.

In such a trajectory, amplitudes, mean values or peaks can be monitored, as depicted in Figure 2.

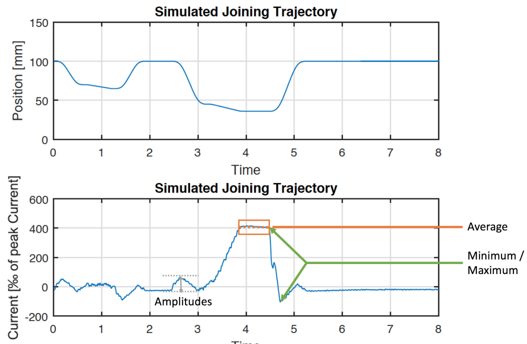

Fig. 2. Typical joining process trajectory

If one of these characteristic points is chosen, the condition monitoring algorithm takes it for every trajectory provided by the data acquisition procedure, and updates its internal statistics for the chosen components. In order to have a unified interpretation procedure, the control chart algorithm is used, as presented by [7]. The control chart algorithm originates from the statistical process control where a manufacturing process is controlled to be stable, based on certain measurement criteria, which are fed into the statistical algorithm.

In the case of this work, this algorithm is used for the calculation of a component's condition. Because the control chart algorithm offers upper and lower stability boundaries for a process, it is applicable to the calculation of a component's condition. The upper and lower boundaries, as proposed by the control chart algorithm, can be used to provide a stability criteria for the health of a component. So for a value which is above the mean value identified by the control chart algorithm, using the upper control boundary (UCB), the condition can be calculated as follows

$$\text{condition} = 100 - \frac{value - mean}{(UCB - mean)} * 100 \quad (4)$$

For values close to the mean value, which are taught, the condition is close to 100, as soon as the taught value reaches the upper control boundary, the condition reaches 0. The same can be done for the lower control boundary. As long as the indicators stay close to the mean, the component is considered healthy (e.g. condition close to 100%). If the indicators leave this area, the condition will get worse until it reaches a critical level (condition equals 0%), which are denoted by the identified control boundaries. With the ongoing research and application of the algorithm, these levels can be taught automatically.

3.1.4. Prediction Algorithm

To predict the time to failure of a component, the calculated condition value is used. The condition value is extrapolated over time, based on the following extrapolation functions:

$$y_N = \Sigma_{i=0}^{N} a_i t^i \tag{5}$$

and

$$y = a(1 - \exp(bt + c)) \tag{6}$$

For the polynomial approach, an order N from 2 to 5 is suitable. In order for the exponential approach to be linear in its parameter, an assumption for the value of a has to be made. Because of the nature of the problem, a denotes the steady state condition at the actual timepoint, and can be estimated using:

$$a_{t^*} = \text{condition}(t^* - 5d) \tag{7}$$

which gives an estimate of the condition 5 days ago. Using this value for a leads to a linear equation system for the exponential approach:

$$\ln(1 - \tfrac{y}{a}) = bt + c \tag{8}$$

The exponential approach is linear in its parameters by design. Using this prediction algorithm, the results, as depicted in Figure 3 were achieved.

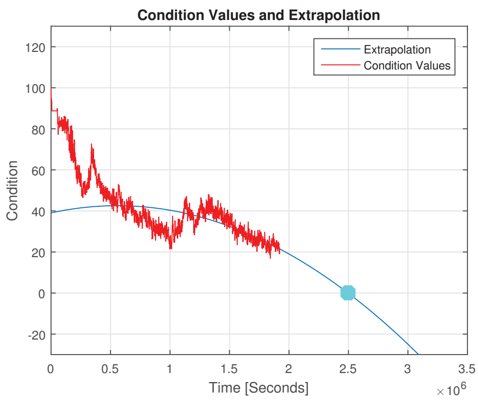

Fig. 3. Prediction trajectory

Figure 3 shows a condition trajectory of a test machine, where a lifetime test was conducted. The plot denotes the prediction of the failure time using the exponential extrapolation function. The extrapolation predicts the condition 0 at the blue point in time in the future. This data can be used to denote the remaining useful lifetime (RUL) of the chosen component. Similar results can be achieved using the polynomial approach. However, the two approaches differ in robustness and quality of extrapolation.

The condition trajectory shows a sharp degradation in a short time period, due to a high load applied to the electrical spindle. The prediction algorithm was able to find a clear failure time.

4. Data Broadcasting and User Interface

To ensure an application of the results, the data needs to be broadcasted to a certain degree. It is important that the production manager of the machine in question has access to this information all the time. The best solution in this case is a web server, containing all useful information, such as the condition, as well as the failure prediction.

However, the user interface can not contain too much information. Data, which is crucial to the company, such as detailed information on the production cycle, sizes and exact product names, can not be displayed, depending on the security issues tied to such information. If data security is an issue, such a web server can be hosted within the companies own network. If the information is displayed as a web based user interface, it is accessible from any computer as well as handheld device. As such, the information can be reached at any time, within certain security boundaries.

The communication procedure is depicted in Figure 4. The proposed architecture is based on a TCP/IP based API. This means that it can be used by any other software tool in order to enhance the productivity of the whole company. SAP and ERP system can access this information in order to plan production batches ahead of time, considering the condition, as well as the failure prediction of each machine.

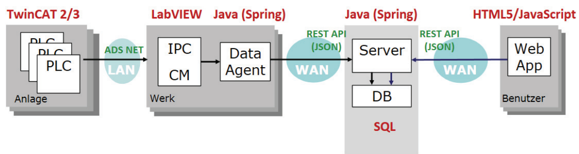

Fig. 4. Broadcasting Procedure

The interfaces, which are used in this concept are completely open source, and are based on a JSON. JSON allows an easy encoding and also readability for debugging and implementation in other software tools. The Representational State Transfer (REST) API principle allows an easy communication structure. Additionally REST API's allow for a seamless integration into a machine-to-machine (M2M) communication network.

5. Application to a test machine

To validate the working algorithm, the application was run on a test machine, where a short time failure test was conducted.

The goal was to test the application of the predictive maintenance algorithm, as well as the communication structure of the application in a real industrial environment. The test machine was set up to match the electronic and mechanic properties of a real machine, currently in use at an industry partner.

The test setup is depicted in Figure 5 and shows the electrical motor, mounted on a spindle axe, which is supported by two guidances. This mechanical setup does not include a gearbox to increase the load on the motor for the test. In order to simulate a high load, such as in a joining process, a mechanical spring is introduced at the bottom of the mechanical movement, which induces loads up to 80% of the maximal motor load.

Both the parameter identification process and the statistical process are run for this setup, which delivered the following results.

5.1. Results

The results, which are presented in this section, are based on a long term failure test on a test machine. This test machine, as depicted in figure 5, was run for two months, in order to get a good insight into the process. The process which was run on the test machine is depicted in figure 2. It simulates a handling movement, between 0 and 2 seconds, and a joining process, with a high torque, between 3 and 5 seconds. This process is run constantly, every 8 seconds to simulate a high load on the axis. In order to have a fast degradation and exceptionally high joining force is chosen, as mentioned before.

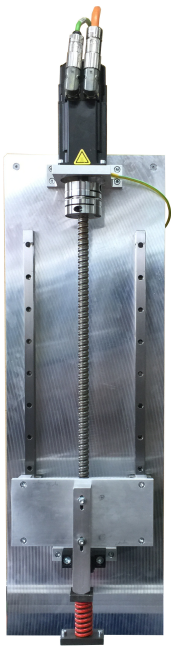

Fig. 5. Mechanical Test Equipment

The chosen point for the analysis is the minimum torque between time points 4 and 5 seconds, meaning the acceleration peak away from the joining process. This peak is at a time, where the axis is not in interference with any workpiece, which means, it is suitable to calculate the condition of the axis. If a different time point were chosen, where the workpiece is in interference with the axis, the condition value can not be calculated only for the axis. If there are any faults in the workpiece, the condition will be influenced, and thus not usable.

The condition value and extrapolation is shown in figure 3. The figure shows the calculated condition over the time of the long term test, as well as the extrapolation function. The extrapolation function shown in this figure is a polynomial approach, which can be seen by the curvature of the function. The polynomial approach, in contrast to the exponential approach is much more resilient to phenomena, such as an increase in condition at $1.3 \cdot 10^6$ seconds.

This behavior can be explained by a change in environmental temperatures during a weekend period, where the windows were continuously opened. Such a change in environmental conditions can not be handled by this algorithm, as they can not be taken into account in a purely statistical approach. If one would take into account environmental condition, data needs to be collected for any possible environmental state, to identify these effects on a statistical basis.

5.2. RUL Estimation Approach

The two extrapolation functions, which are proposed in this paper are a polynomial and an exponential approach, the two approaches estimate the RUL quite well, however, the nature of the exponential approach can not handle increasing conditions in the way it is modelled. Thus, effects such as the two condition increases as depicted in figure 3 at time points $0.3 \cdot 10^6$ and $1.3 \cdot 10^6$ can not be handled.

The resulting RUL predictions of both prediction approaches are depicted in figures 6 and 7. Both figures show the predicted failure time at any given time point during the test. The resulting RUL is calculated form the extrapolation as depicted in Figure fig:pred1, where the condition reaches 0. Depending on the risk awareness of the machine operator, the threshold can be adjusted. Because the extrapolation is implemented recursively, a new RUL estimation is produces every time a new trajectory is recorded. Because the exponential extrapolation is more robust to environmental changes, it shows a more continuous trajectory.

The polynomial approach, which can handle increasing condition values by not proposing any RUL at all, shows no RUL prediction in the uncertain period.

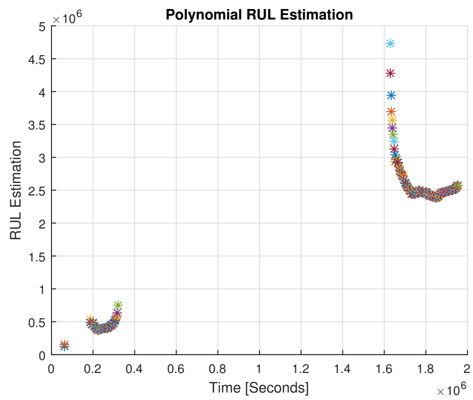

Fig. 6. Condition Trajectory and Extrapolation

Because for the exponential approach the RUL estimation is increasing at a steady rate, it can lead to unwanted behaviour, as is is continuously issuing warnings that a failure is about to occur. For the polynomial approach, uncertain changes in condition will result in an uncertain prediction, which leads to no RUL prediction. This means, that no unwanted behaviour can be observed in this time period.

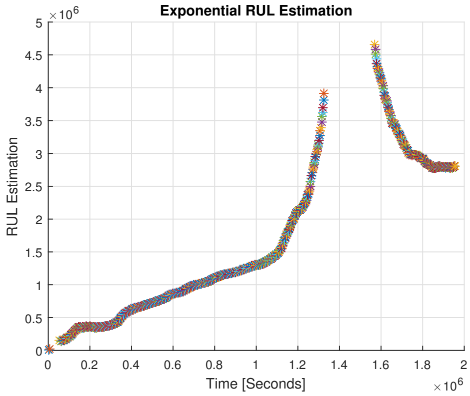

Fig. 7. Condition Trajectory and Extrapolation

However, the steady state value is approximately the same in the end, only differing 12-24 hours. For a large scale production environment, the maintenance can be planned in the production schedule, and should be considered a few days before the imminent failure time.

6. Concluding Remarks

The proposed framework works well on the test machine and could be implemented on a real machinery in a production environment. However, due to the slower degrading of the production environment, no failure could be detected yet.

The application of the algorithms is automated, such that the end user can apply it to any machine without effort. To display the data in a meaningful way, a web interface was introduced, as depicted in figure 8.

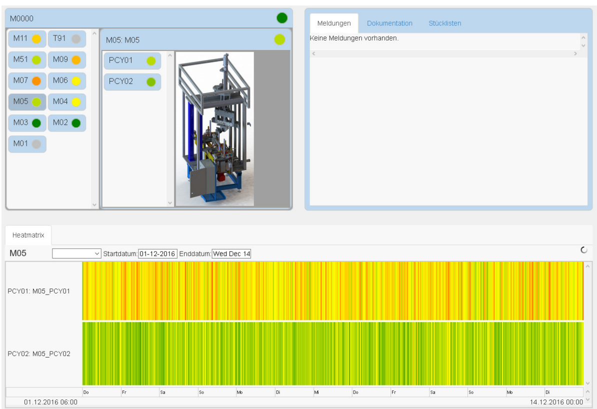

Fig. 8. Webinterface

The web interface eases the application of the prediction algorithm to the end user, such as the maintenance team. It displays time to failure and the current condition. Further, information such as the wear and energy consumption, depending on the product can be displayed. Although not crucial to the condition monitoring system, this information is a byproduct of the algorithm, which helps with product development or similar.

6.1. Conclusion

The application of the algorithm shows, that the condition monitoring and the prediction can actually foresee a degradation and specify the time point, where the degradation has reached its critical value. However, due to lack of data, which needs to be collected over a timespan longer than a year, this critical degradation can not be specified at this point in time.

The application of such systems, will however generate the much needed data, in order to specify such margins in much more detail than nowadays, based on real world failures, which can be tied to the monitored data.

6.2. Outlook

To improve and further develop the condition monitoring and prediction algorithm for this application, further insight into real failures has to be gathered. The difference to test stand failures, which are induced based on a physical understanding of wear and motor load, industry applications tend to differ a lot.

Human induced errors and breakdowns are frequent, as well as changing environmental conditions, wrong usage and greasing as well as different kinds of dirt. Such errors are hard to model as they are induced by human error, but are crucial to the lifetime and condition of each component. A long time data acquisition and data analysis in an industrial environment would be the next step to further improve the information on that matter.

References

[1] Engeler, M., Elmiger, A., Zogg, P.D.D., Kunz, P.D.A., Wegener, P.D.K.. Condition-based Maintenance: Model vs. Statistics A Performance Comparison; vol. ? of *?* Elsevier; 2017.

[2] Jeong, Y.S., Lee, J.Y.. Parameter identification of an induction motor drive with magnetic saturation for electric vehicle. Journal of Power Electronics 2011;.

[3] Völlmecke, I.. Parameter identification of dc motors. Tech. Rep.; imc-berlin; 2013.

[4] Shaw, S.R.. Numerical methods for identification of induction motor parameters. Ph.D. thesis; Massachusetts Institute of Technology; 1995.

[5] Schoen, R.R., Habetler, T.G., Kamran, F., Bartheld, R.G.. Motor bearing damage detection using stator current monitoring. IEEE Transactions on Industry Applications 1995;.

[6] Choi, S., Baek, J.. Iterative condition monitoring and fault diagnosis scheme of electric motor for harsh industrial application. IEEE Transactions on Industrial Electronics 2015;.

[7] Montgomery, D.C.. Introduction to Statistical Quality Control. 2008; Wiley.

[8] Stuber, B.. Hocheffiziente, modulare elektroantriebssysteme hoher leistungsdichte - grundlagen vektorregelung. Fachhochschule Nordwestschweiz; 2013.