Synthetic Data for Hybrid Prognosis

Madhav Mishra[1], Urko Leturiondo[2], and Diego Galar[3]

[1,3] *SKF-University Technology Centre, Luleå University of Technology, Luleå, 971 87, Sweden*
madhav.mishra@ltu.se

[1,2,3] *Division of Operation and Maintenance Engineering, Luleå University of Technology, Luleå, 971 87, Sweden*
diego.galar@ltu.se

[2] *Mechanical Engineering, IK4-Ikerlan, Arrasate-Mondragon, Gipuzkoa, 20500, Spain*
uleturiondo@ikerlan.es

ABSTRACT

Using condition-based maintenance (CBM) to assess machinery health is a popular technique in many industries, especially those using rotating machines. CBM is relevant in environments where the prediction of a failure and the prevention and mitigation of its consequences increase both profit and safety. Prognosis is the most critical part of this process and the estimation of Remaining Useful Life (RUL) is essential once failure is identified. This paper presents a method of synthetic data generation for hybrid model-based prognosis. In this approach, physical and data-driven models are combined to relate process features to damage accumulation in time-varying service equipment. It uses parametric models and observer-based approaches to Fault Detection and Identification (FDI). A nominal set of parameters is chosen for the simulated system, and a sensitivity analysis is performed using a general-purpose simulation package. Synthetic data sets are then generated to compensate for information missing in the acquired data sets. Information fusion techniques are proposed to merge real and synthetic data to create training data sets which reproduce all identified failure modes, even those that do not occur in the asset, such as Reliability Centered Maintenance (RCM), Failure Mode and Effect Analysis (FMEA). This new technology can lead to better prediction of remaining useful life of rotating machinery and minimizing and mitigating the costly effects of unplanned maintenance actions.

1. INTRODUCTION

The use of Condition-Based Maintenance (CBM) has increased rapidly over recent years, largely because CBM can predict failure in such a way that the profit and safety of the asset are increased. Once failure occurs, however, it is crucial to continue the prognosis process, estimating the Remaining Useful Life (RUL) of the asset.

Physical or theoretical models can be used for this purpose. Theoretical models are determined from the physics of the system and expressed by means of equations (Isermann & Münchhof, 2011). These equations, either ordinary or partial differential equations, can be classified as the following:

- Balance equations (i.e. chemical reactions)
- Physical or chemical equations of state (i.e. equations that relate state variables)
- Phenomenological equations (e.g. Fourier's law of heat conduction)
- Interconnection equations (e.g. Kirchhoff's current law)

Once a set of equations is obtained, the theoretical model is defined. Complex equations are simplified by means of linearizations, approximations with lumped parameters, and order reductions, among others (Isermann & Münchhof, 2011), making mathematical treatment feasible.

These models are very useful for describing the behaviour of time-varying systems, taking into account different operating modes, transients, and variability in environmental conditions. The greater the complexity of the model, the greater the effort required to develop and validate it (Galar, Kumar, Villarejo, & Johansson, 2013). This calls for more computational resources. Thus, a limit in the complexity of the physical model should be defined.

There are many physical models used for rotating machinery. (Qiu, Seth, Liang, & Zhang, 2002) simplify a bearing as a single Degree-of-Freedom (DOF) model using a mass-spring-damping system. (Harsha, 2006) and (Purohit & Purohit, 2006) take a 2 DOF approach when modelling a bearing to study the motion of the shaft in the plane of the bearing. Other authors such as (Jain & Hunt, 2011) consider the dynamics of the rolling elements of a bearing by using a 3 DOF model for the shaft and a 2 DOF model for each ball.

(Sawalhi & Randall, 2008) develop a 5 DOF model for a rolling element bearing in which they consider the rolling elements as angularly equidistant; they also propose a 6 DOF model for a gear, and use the model to obtain the response of a gearbox test rig. The work of (Baguet & Jacquenot, 2010) combines a shaft-gear model and hydrodynamic journal bearing model. In this case, a pinion-gear pair is represented by means of two shaft finite elements with two nodes each; the stiffness is calculated taking into account the tooth deflection and the foundation flexibility. (Abbes, Hentati, Maatar, Fakhfakh, & Haddar, 2011) present a model that combines the dynamics of a ball bearing and a gear transmission. They introduce a time-varying stiffness matrix, where the number of teeth in contact and the variability of periodic and mesh-frequency based mesh stiffness are considered as varying parameters.

In all these approaches, a system model is at the centre of the development process, from requirements analysis, through design, implementation and testing. Today, nevertheless, the model-based approach is also designed for maintenance purposes, especially condition monitoring. The main advantage of these approaches to CBM over data-driven approaches is their ability to incorporate a physical understanding of the monitored system (Luo et al., 2003). Data-driven models miss the link between data and the physical world, thus questioning the reliability of the algorithm, but physical models make the prediction of results intuitive because of their use of case-effect relationships. Their main drawback is the effort required to develop them. Moreover, they require assumptions regarding complete knowledge of the physical processes; parameter tuning may require expert knowledge or learning from field data. Finally, high fidelity models may be computationally expensive to run.

2. MODELLING FAILURES

Physical models are used to estimate the response of systems in both healthy conditions and failure conditions. The models can be used to simulate component or system failures, and with adequate modelling of the failure modes, the model can be adjusted. In other words, different system responses can be obtained, with and without failure, using the equation set forming the physical model.

The literature notes several ways of modelling failure in the field of rotating machinery. For example, (Rafsanjani, Abbasion, Farshidianfar, & Moeenfard, 2009) reproduce the transient force that occurs when a rolling element bearing comes into contact with a defective surface creating a series of impulses that repeat the characteristic frequencies of the elements of the bearing. (Kiral & Karagülle, 2003) amplify the contact forces using a predefined constant when the bearing contact is produced in a damaged area.

(Nakhaeinejad, 2010) proposes modelling faults as surface profile changes instead of introducing mathematical impulse functions based on fault frequencies. (Tadina & Boltežar, 2011) develop a 2D model of a bearing in which defects are modelled as geometric changes. In this case, a fault in a race is modelled as an ellipsoidal depression whereas a fault in a ball is modelled as a flattened sphere.

For fault modelling of gears, (Chen & Shao, 2011) develop a mesh stiffness model in which a gear tooth is divided into thin pieces; the stiffness of each piece is calculated taking into account bending, shear and axial compress (function of fault properties). Then, the whole tooth stiffness is obtained by integrating the stiffness of each slide. (Jiang, Shao, & Mechefske, 2014) introduce spalling faults in a gear model as a variation in the mesh stiffness of the teeth contact. The length of the contact line is modified to change the value of the stiffness.

However, it is difficult to predict the RUL once there is a spall in the system. Thus, failure evolution and how some failure modes initiate or aggravate others should be defined. Crack propagation failure modes are the most commonly developed behavioural models for prognostics (Sikorska, Hodkiewicz, & Ma, 2011). For example, the Paris-Erdogan law (Paris & Erdogan, 1963) can be used to define the evolution of the growth of a sub-critical crack under a fatigue stress regime and is expressed as:

$$\left(\frac{da}{dN}\right)_{n+1} = C \cdot (\Delta K)^m \qquad (1)$$

where a is the crack length, N is the number of load cycles, n is the current iteration, ΔK is the range of the stress intensity factor, and C and m are material constants. Following this theory, as well as Forman and NASGRO 2/3 laws, (Drewniak & Rysiński, 2014) provide an analytical gear teeth fatigue life estimation. (Li, Kurfess, & Liang, 2000) use a stochastic defect-propagation model to calculate the RUL of a bearing.

3. CREATION OF DATA SETS

System prognosis requires data which can be obtained from two sources: an operating system using different sensors or a physical model. In certain cases, the latter source has some advantages, as for example, the case of an aircraft.

Data from an aircraft system can be recorded when the asset is healthy, but once the Key Performance Indicator (KPI) of the system reaches the maintenance threshold limit, maintenance processes are carried out. Thus, data can only be acquired until near time t_m, the time when the limit is crossed, taking into account some tolerance, as shown in Figure 1. The asset

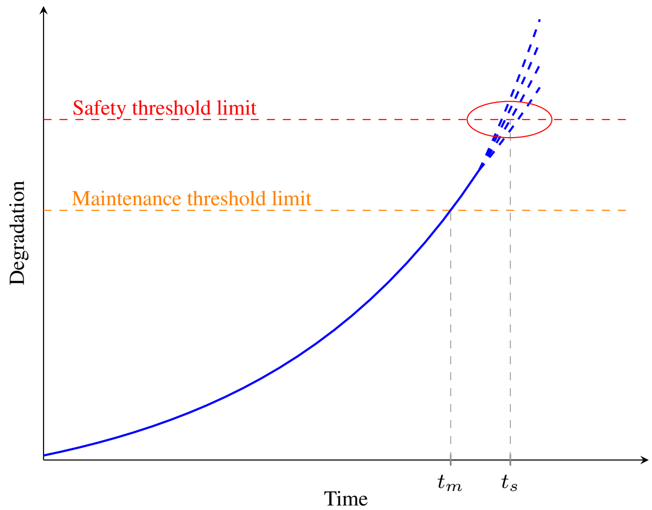

Figure 1. Trend analysis for the remaining useful life

will never be allowed to exceed the predefined safety threshold limit (reached at an unknown time t_s) for the following reasons:

- Security: some faults put both the asset and the people using it at risk.
- Cost: the development of a fault in a component of an aircraft can be very expensive.
- Environmental issues: the effect of a fault can be detrimental for the environment.

Consequently, faulty conditions cannot be recorded from the real system. However, such data can be created with a physical model. Failure modes can be defined using Reliability Centred Maintenance (RCM) and Failure Mode and Effect Analysis (FMEA), among others. When these failure modes are modelled, the data generated are called "synthetic" data.

In conclusion, the final data set is formed by data generated from both real systems and a physical model of the system. As both physical-model and data-driven approaches are used, a hybrid model is formed, as illustrated in Figure 2.

3.1. Semi-supervised learning

Classification techniques are divided into three groups: unsupervised, supervised and semi-supervised learning. Unsupervised classification or cluster analysis consists of a set of techniques used to group individuals in unknown groups. The objective is to relate p individuals to q groups in such a way that each element is associated with only one group and the distribution of each group is internally homogeneous. Supervised learning, also known as machine learning, begins with data that belong to 2 or more groups. The objective is to obtain a relationship between the inputs (data) and the outputs (groups) in such a way that it is possible to assign a group to a new data case.

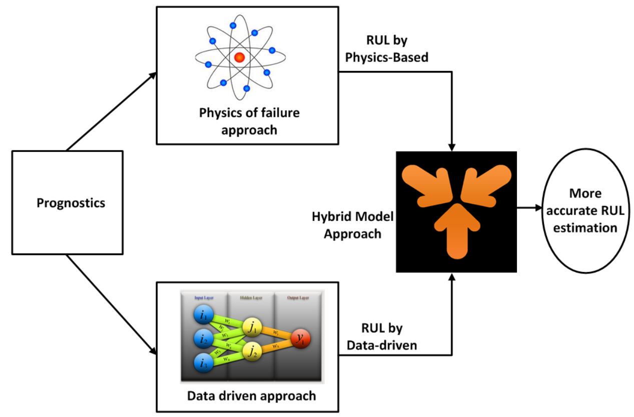

Figure 2. Hybrid model approach

Semi-supervised learning falls between the two other methods. Looking again at the aircraft, data can only be recorded when the system is healthy. Figure 3 shows some healthy data taking into account two features. Newly acquired data near the individuals in Figure 3 will belong to the healthy case, but if not they will belong to a faulty case. Therefore, only healthy and faulty cases can be distinguished.

Faulty data cannot be captured from the aircraft because of the reasons already presented. When synthetic data are generated by a physical model, however, different failure modes can be recognized besides the healthy case. This improves the initial classification criterion. Data belonging to healthy (H) and some faulty cases (F_1, F_2 and F_3) can be seen in Figure 4. Newly acquired data will belong to any of these cases.

Once the data set is created, semi-supervised learning is carried out using such techniques as Support Vector Machine

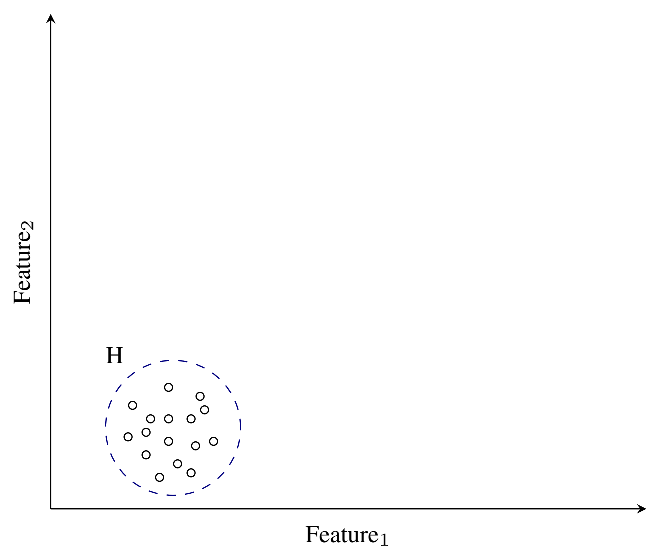

Figure 3. Learning using healthy data recorded from the real system

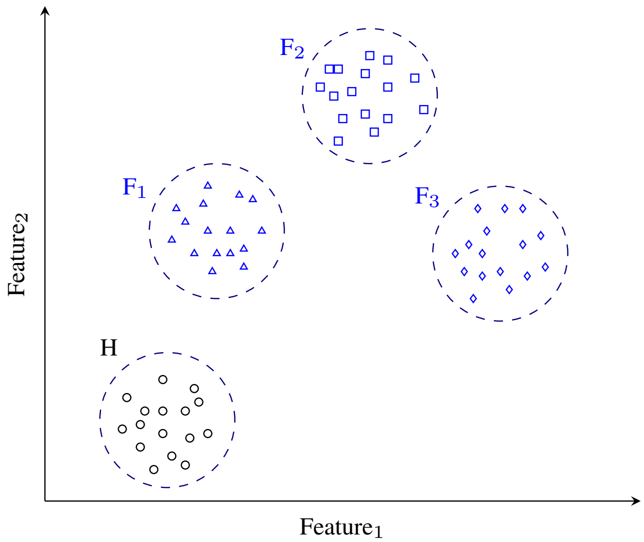

Figure 4. Learning using both healthy data acquired from the real system and synthetic data generated by the physical model

(SVM), k Nearest Neighbour (kNN) and Neural Networks (NN), among others.

4. TUNING PROCESS

When the learning process is completed, newly acquired data can easily be classified using the aforementioned methods. However, data that do not fit into any of the clusters defined in the learning process can also appear. This state in which an abnormal or unknown fault is produced is known as No-Fault-Found (NFF). A graph illustrating this is shown in Figure 5. Here, the new data do not belong to any of the predefined groups (H, F_1, F_2 and F_3) are labelled NFF. There are two main reasons for the appearance of NFF data:

- The physical system is not sensitive to one of the studied failure modes, and the acquired data do not reflect the response of the physical system.
- The acquired data belong to a failure mode not previously identified.

The appearance of this kind of data must be used to update the already established classification criteria. They are considered data related to another failure mode, and the semi-supervised learning is repeated. The process of automatically updating the classification criteria is called the tuning process. A scheme of this process appears in Figure 6. New data acquired from the real system are considered input data and are classified according to the clusters previously obtained using synthetic and raw data. The output is used to retrain and improve the classification method.

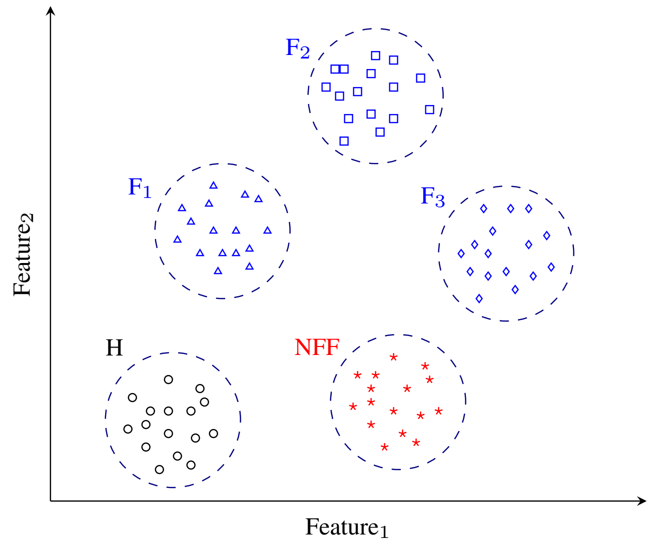

Figure 5. No-fault-found case

Once the tuning process is developed, it gives a better understanding of failure evolution; consequently, the prognostics process is more easily carried out.

5. CONCLUSIONS

The main purpose of the hybrid model is to compensate for the weaknesses of data driven and physical models. Data-driven techniques are based on complete data sets that do not usually cover all the identified failure modes because of economic, security or environmental reasons. Additional data are needed from models based on knowledge to fill the gap. Physical models are able to represent the response of a system in

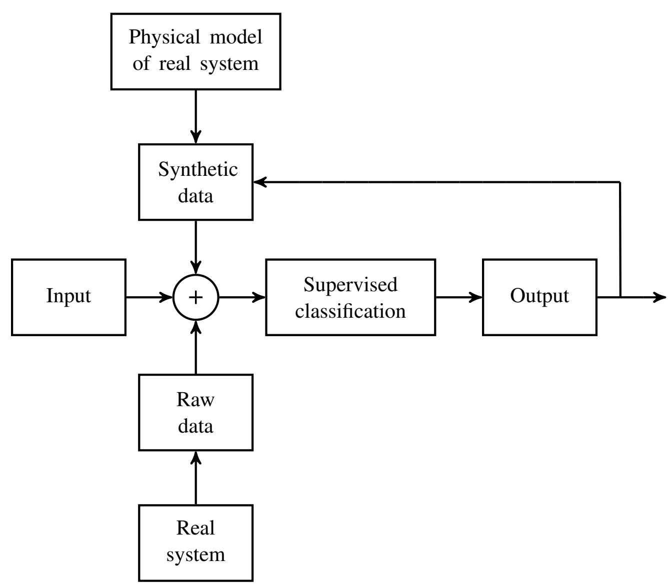

Figure 6. Tuning process of the classification method

normal operating conditions and include fault modelling with the objective of determining the behaviour of the system in different faulty cases detected by different failure mode analyses. It is not new to get data from physical models, but the way these data are integrated in the system and how the physical model is tuned to increase the accuracy of these synthetic data are certainly new. In addition, the system must be able to produce data for all the failure modes identified by means of FMEAs and other failure analysis techniques.

As a consequence of this interaction, "synthetic" data sets are created. These, in combination with raw data acquired from the real system, can be used in semi-supervised learning to improve the accuracy of estimations using only the real data. When newly acquired data suggest the presence of a failure that has not been considered, the data are used to update the learning process. The goal is to create the most complete date sets covering all relevant failure modes to obtain better remaining useful life estimation.

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REFERENCES

Abbes, M. S., Hentati, T., Maatar, M., Fakhfakh, T., & Haddar, M. (2011). Dynamic analysis of helical gears supported by rolling element bearings. *Journal of Theoretical and Applied Mechanics*, *41*, 33-50.

Baguet, S., & Jacquenot, G. (2010). Nonlinear couplings in a gear-shaft-bearing system. *Mechanism and Machine Theory*, *45*(12), 1777-1796.

Chen, Z., & Shao, Y. (2011). Dynamic simulation of spur gear with tooth root crack propagating along tooth width and crack depth. *Engineering Failure Analysis*, *18*(8), 2149-2164.

Drewniak, J., & Rysiński, J. (2014). Model of fatigue damage accumulation. *Key Engineering Materials*, *598*, 51-56.

Galar, D., Kumar, U., Villarejo, R., & Johansson, C.-A. (2013). Hybrid prognosis for railway health assessment: an information fusion approach for PHM deployment. *Chemical Engineering Transactions*, *33*, 769-774. (PHM 2013 - Special Issue)

Harsha, S. P. (2006). Nonlinear dynamic analysis of rolling element bearings due to cage run-out and number of balls. *Journal of Sound and Vibration*, *289*(1-2), 360-381.

Isermann, R., & Münchhof, M. (2011). *Identification of dynamic systems - An introduction with applications*. Springer Berlin Heidelberg.

Jain, S., & Hunt, H. (2011). A dynamic model to predict the occurrence of skidding in wind-turbine bearings. *Journal of Physics: Conference Series*, *305*(1), 012027.

Jiang, H., Shao, Y., & Mechefske, C. K. (2014). Dynamic characteristics of helical gears under sliding friction with spalling defect. *Engineering Failure Analysis*, *39*, 92-107.

Kiral, Z., & Karagülle, H. (2003). Simulation and analysis of vibration signals generated by rolling element bearing with defects. *Tribology International*, *36*(9), 667-678.

Li, Y., Kurfess, T. R., & Liang, S. Y. (2000). Stochastic prognostics for rolling element bearings. *Mechanical Systems and Signal Processing*, *14*(5), 747-762.

Luo, J., Namburu, M., Pattipati, K., Qiao, L., Kawamoto, M., & Chigusa, S. (2003). Model-based prognostic techniques [maintenance applications]. In *AUTOTESTCON 2003. IEEE Systems Readiness Technology Conference. Proceedings* (p. 330-340).

Nakhaeinejad, M. (2010). *Fault detection and model-based diagnostics in nonlinear dynamic systems* (Unpublished doctoral dissertation). The University of Texas at Austin.

Paris, P., & Erdogan, F. (1963, December). A critical analysis of crack propagation laws. *Journal of Basic Engineering*, *85*, 528-533.

Purohit, R. K., & Purohit, K. (2006). Dynamic analysis of ball bearings with effect of preload and number of balls. *International Journal of Applied Mechanics and Engineering*, *11*(1), 77-91.

Qiu, J., Seth, B. B., Liang, S. Y., & Zhang, C. (2002). Damage mechanics approach for bearing lifetime prognostics. *Mechanical Systems and Signal Processing*, *16*(5), 817-829.

Rafsanjani, A., Abbasion, S., Farshidianfar, A., & Moeenfard, H. (2009). Nonlinear dynamic modeling of surface defects in rolling element bearing systems. *Journal of Sound and Vibration*, *319*(3-5), 1150-1174.

Sawalhi, N., & Randall, R. (2008). Simulating gear and bearing interactions in the presence of faults: Part I. the combined gear bearing dynamic model and the simulation of localised bearing faults. *Mechanical Systems and Signal Processing*, *22*(8), 1924-1951.

Sikorska, J. Z., Hodkiewicz, M., & Ma, L. (2011). Prognostic modelling options for remaining useful life estimation by industry. *Mechanical Systems and Signal Processing*, *25*(5), 1803-1836.

Tadina, M., & Boltežar, M. (2011). Improved model of a ball bearing for the simulation of vibration signals due to faults during run-up. *Journal of Sound and Vibration*, *330*(17), 4287-4301.

BIOGRAPHIES

Madhav Mishra is a PhD Researcher at Luleå University of Technology, Luleå (Sweden), within the framework of the SKF-University of Technology Centre (UTC) at the Division of Operation and Maintenance Engineering. His research focus lies to improve the diagnosis and prognosis of the RUL of an asset by the development of hybrid models. He obtained Master degree in Control Systems Engineering with specialisation in Mechatronics from the Netherlands. He worked at Philips Semiconductors/NXP in Nijmegen in the Netherlands as a Senior Design Engineer Mechatronics where he has involved in design and developed of the high speed rotating machine.

Urko Leturiondo obtained his M.Sc. in Mechanical Engineering from Tecnun, Engineering School of the University of Navarra (Spain). He joined IK4-Ikerlan in 2012 as a PhD student, doing his research on the topic of condition-based maintenance of rolling element bearings. Actually he carries out this research work in collaboration with the Division of Operation and Maintenance Engineering, Luleå University of Technology, Luleå (Sweden).

Diego Galar has a M.Sc. in Telecommunications, PhD degree in Manufacturing from the University of Saragossa and PhD in BA from Mexico V. University. He has been Professor in several universities, including the University of Saragossa or the European University of Madrid, a senior researcher in I3A, Institute for engineering research in Aragon, director of academic innovation and subsequently pro-vice-chancellor. He has also been visiting Professor in the University of Valencia, Polytechnic of Braganza (Portugal), Valley University (Mexico) and NIU (USA). In Industry, he has been technological director and CBM manager. He has authored more than hundred journal and conference papers, books and technical reports in the field of maintenance. Currently, he is full professor in the Division of Operation and Maintenance Engineering in LTU, Luleå University of Technology, where he is coordinating several EU-FP7 projects related to different maintenance aspects and is also involved in the in the SKF UTC centre located in Luleå focused in SMART bearings.