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# A Framework for Data Integration and Analysis in Radial-Axial Ring Rolling

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**Abstract**

Data-driven analytical approaches such as machine learning bear great potential for increasing productivity in industrial applications. The primary requirement for using those approaches is data. The challenge is to not only have any kind of data but data which has been transformed into an analytically useful form. Building upon this initial requirement, this paper presents the current state concerning data analysis and data integration in the industrial branch of hot forming, specifically focussing on radial-axial ring rolling. The state of the art is represented by the results of a data survey which was completed by six of Germany's representing radial-axial ring rolling companies. The survey's centre of interest focuses on how data is currently stored and analysed and how it gets depicted into eight different statements. Based on the results of the survey a framework is proposed to integrate data of the whole production process of ring rolling (furnace, punch, ring rolling machine, heat treatment and quality inspection) so that data-driven techniques can be applied to reduce form and process errors. The proposed framework takes into account that a generalized standard is hard to set because of already grown structures and a huge variety of analytical methods. Therefore, the framework focuses on data integration issues commonly found in an industrial setting as opposed to controlled research environments. The paper proposes methodologies on how to utilize the potential of each company's data. As a result, the proposed framework creates awareness for saving the data in a standardized and thoughtful manner as well as building a data-driven culture within the company.

**Keywords**

Machine learning; Data integration; Framework; Radial-axial ring rolling

## 1. Introduction

In times of 33 Zettabytes of digital data in 2018 and a predicted growth to 175 Zettabytes by 2025 referring to a white paper of the International Data Corporation, there seems to be a high demand for analytical approaches to face those enormous amounts of information [1]. In recent years, the usage of machine learning especially supervised methods are heavily researched and used in several industrial solutions. One of the biggest restrains to use and benefit from these techniques is the demand for a lot of data in an analytically useful forms. Today, many companies are already saving a lot of their information and storing it, for example in a huge data lake, but only a few have defined production goals in mind while storing this data. A survey carried out by MicroStrategy in 2018 shows that the majority of the participants state the need to drive strategy and change as their primary focus followed by industrial/manufacturing improvements for data analytics in Germany [2]. This leads to a status quo where data is accessible but often not useful because of several striking issues concerning the form in which the data is stored. In this paper the status quo within the hot forming sector, specifically the radial-axial ring rolling (RARR) is being investigated by displaying the results of a data survey which was carried out in 2019 and six of Germany's representing ring rolling companies which participated in the survey. The results are discussed and a framework on how to store and integrate data the right way for further analysis it is proposed. This framework will be used to analyse process and form errors of the rolled ring (e.g. climbing, non-circularity, fish-tail [4]) using methods of machine learning for time series and sequence data. The high complexity of the ring rolling process and thereby high amount of influencing variables suggest the approach of using machine learning.

The paper highlights common mistakes made during the process of storing data and proposes ways to overcome these issues while presenting a best practice advice for companies in the hot forming industry. The biggest problem concerning this issue are grown structures in each company which makes it hard to propose a standardized framework for every industry. Further, the different data types (structured, semi-structured and unstructured [3]) that arise in the different areas of industry aggravate the challenge of coming up with one standardized way to tackle this challenge. This is the reason why to the best of the author's knowledge there is no such thing as a sole standard for data integration in ring rolling or similar processes.

The paper starts by focusing on related work in RARR and other fields of production engineering, machine learning for time series and data integration frameworks. It follows up with the introduction to the industrial process of RARR and presents the carried out survey. Based upon this, the survey is discussed and used as a starting point for the proposed framework for data integration and analysis in RARR. The paper closes with a section regarding the desired deployment of the proposed framework in two industrial companies.

## 2. Related Work

### 2.1 RARR and production engineering

First approaches of using process data to evaluate the ring rolling process regarding its process and form errors were made by the *Lehrstuhl für Produktionssysteme.* The potential to classify process-failures, such as ring-climbing, using data mining techniques (fuzzy-logic) has already been shown in 2004 by LAGAO [5]. HUSMANN ET AL. used process-data in form of structured log-files from a ring rolling machine to avoid ovality of the ring [6]. Additionally, HUSMANN ET AL. analysed the ring rolling process further by using image data as well as thermography data in different ways, producing unstructured data regarding the ring rolling process [7,8]. Similar to those approaches for RARR, WANG ET AL. use support vector machines to reach up to 95 percent classification accuracy in equipment failure classification for optical networks [9].

Besides those approaches for process failure prediction, machine learning is used in a variety of applications throughout other fields of production engineering and not all can be addressed during this paper. The paper focuses only on current implementations of predictive maintenance and optical quality inspection in production engineering environments. For example, LEE ET AL. use support vector machines as well as deep learning networks to model the remaining useful lifetime of a machine tool system [10]. In contrast, WÖSTMANN ET AL. present an implementation of a predictive maintenance system using neural networks, decision trees, random forests and other algorithms for a retrofit robotic cell [11].

Another field of operation is optical quality inspection using machine learning models. MAYR ET AL. use machine learning algorithms to classify welding defects for a quality monitoring system [12]. A different approach to analyse computed tomography images using a pre-trained neural network (AlexNet) is proposed by HALWAS ET AL. to validate the layer structure of windings in the automotive sector [13].

### 2.2 Machine Learning for time series

Regarding current research in the area of time series classification, FAWAZ ET AL. make use of different approaches using Deep Neural Networks [14]. A more specific approach to time series classification is reviewed by SANTOS AND KERN as well as RUßWURM ET AL. with regards to early classification time series

(ECTS), which enable the algorithms to classify process data on-line [15,16]. Regarding the RARR process, faults and failures are heavily under sampled. As a result, HE ET AL. propose an ensemble of classifiers to work on the challenge of imbalanced datasets for ECTS [17].

### 2.3 Frameworks

To the best of the author's knowledge regarding modern frameworks for data integration and analysis in the area of RARR no prior research was found which implies the assumption that the presented approach is the first in RARR. Regarding other fields of the industry, there is a lot of related work that has been done on the issue at hand. Much research can be found in the field of medicine and healthcare, for example PERAL ET AL. propose an ontology based architecture to deal with the unique requirements of data in combination with Telemedicine Systems [18]. EL ABOUDI AND BENHLIMA reviewed popular healthcare monitoring systems and propose an approach which is focused more on the big data aspect of healthcare [19]. Further, SAMOURKASIDISA ET AL. propose a framework for environmental data and discuss different approaches to solve the problem of data heterogeneity [20].

## 3. Motivation

### 3.1 Radial-axial ring rolling

Many machines and systems in the aerospace and energy industry need seamless formed rings made of steel, aluminum or nickel, which additionally need to satisfy high standards e.g. highly dynamic load capacity and high variability. A majority of those high-performance rings are being formed through the hot forming process RARR. This process can form seamless rings ranging from 100 mm to 16 m in diameter to a maximum wall height of up to 4 m. The weight can vary between a few kilogram to up to 300 t [21]. Applications of ring rolled rings can be found in the automotive, the aerospace and rail traffic sectors. The importance of RARR within Germany is depicted in an Euroforge-survey from 2016, which states that with 156.000 t half of all open die forged rings were made using RARR [22]. The whole process of RARR consists of five main production steps. A blank is cut from raw material and is usually heated up to forging temperatures ranging from 1000 °C up to 1300 °C depending on the materials that are being used. The hot blank is then pierced by a punch to create the preform of the ring. During the rolling process, the ring is formed simultaneously in two opposing located radial and axial rolling gaps. The radial rolling gap consists of a driven main roll in collaboration with a non-driven mandrel. The mandrel's purpose is to continuously move towards the main roll translational to lower the rings wall thickness by pressing the ring against the main roll. On the opposing side, the axial rolling gap consists of two driven conical rolls. A downwards movement of the upper axial roll towards the lower roll realises the reduction of the ring's height. Due to the constancy of material volume, the ring is continuously and primarily growing in its diameter. The axial rolling gap is then steadily moving away from the radial rolling gap to ensure an optimal rolling position synchronised to the ring's diameter growth. To increase stability during the whole process, two guide rolls are located besides the radial rolling gap to stabilize the ring. The formed ring is then cooled off and a first quality inspection is being run. Depending on the use-case of the ring, it might undergo another production step of heat treatment (e.g. stress-relief annealing and tempering). The last step in the process flow is a final quality inspection. This can range from automated ring measuring to crack testing, using ultrasonic methods. The whole production flow is depicted in Figure 1.

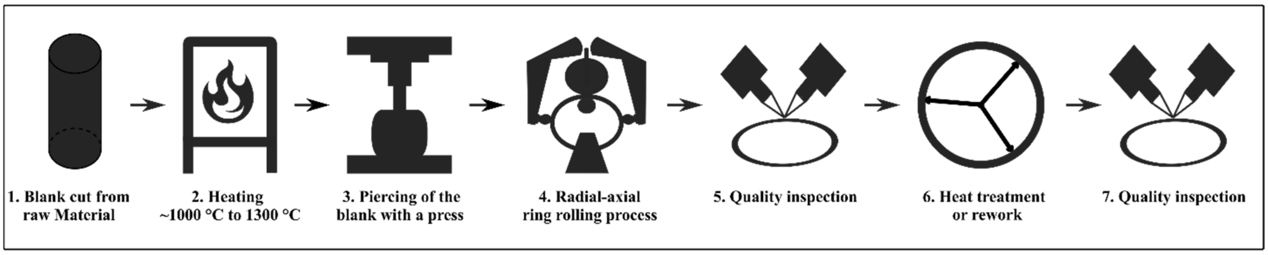


Figure 1: Production flow in RARR

Regarding all steps of the whole production chain, this paper looks at the current state of the art of data management and data analysis in the forming step (step 4 in Figure 1). This is done by presenting the results of a survey made in 2019 in which six representing ring rolling companies situated in Germany were interviewed regarding data storage and data analysis in the ring rolling process. The results of the survey are examined and a standardized framework of how to store and merge data in the ring rolling process is proposed in this paper.

### 3.2 Data Survey

The carried out data survey consists of eight different statements:

1. Process data is measured and stored
2. Process data is used and analyzed
3. Data is saved in a database
4. Data is (additionally) stored in its raw-format
5. Data is stored regarding common standards
6. Data is stored regarding internal standards
7. Operating data (e.g. tool replacements) are digitally tracked and stored
8. The whole production chain is connected and produced data is relatable

The results of the whole survey are shown in Figure 2. Possible answers to the statement were “yes”, ”no” and “no information”.

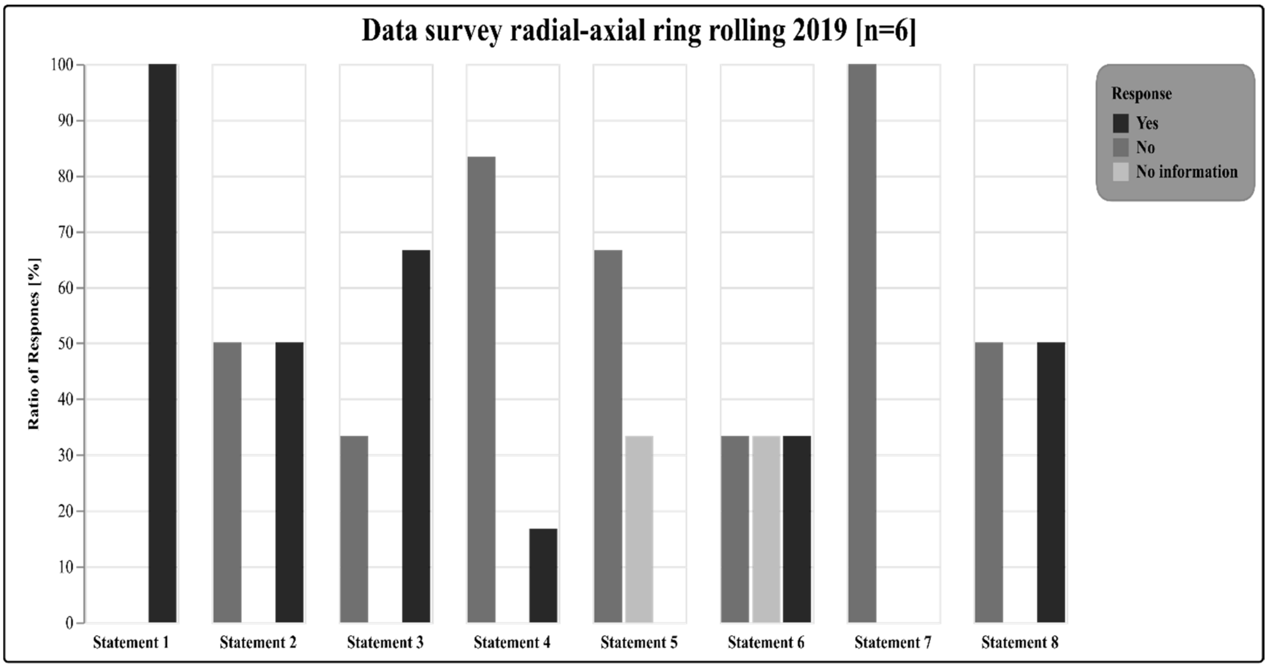


Figure 2: Data survey results 2019 showing all data

The overall result of the survey shows that six out of eight statements were answered with different responses, which indicates a mixed state of the art throughout all participants. Taking a closer look at groups of statements and their responses gives additional useful insights. To do so, the responses of statement one and two as well as the responses of statement three and four are depicted in Figure 2.

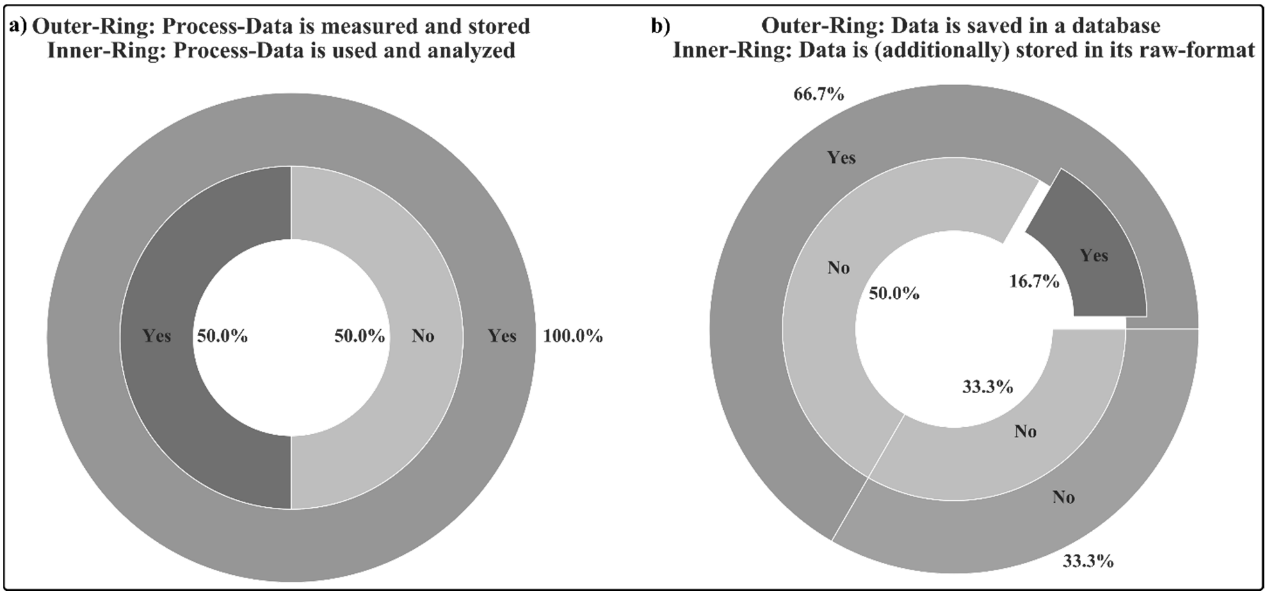


Figure 3: a) Result of statements 1 and 2; b) results of statements 3 and 4

As seen in Figure 3a, statements one and two were particularly asked to elaborate the state of the art concerning data acquisition in RARR. The responses show that all companies do measure and store the process data but only half of them are actually taking a look at the data and are using it for analysis. That means that at least 50 percent of the companies do not recognize whether the stored data is in the right format, has all the necessary features or might eventually be measured in an accuracy which is too low to represent the meant information. Especially the last aspect is a common mistake that, once data is being saved, is never revised and validated. Regarding the responses of statement three and statement four in Figure 3b, a positive aspect is, that in 66.7 percent the data is already stored in a database and not in files on local servers all over the production environment. A downside of the responses is that only 16.7 percent store the data in a database in its raw-format, which means that the data is not aggregated or modified in any way. The storage of data in its raw-format will also be discussed later on as it is one key aspect for a convenient data integration framework. The last aspect of the survey, statement seven, needs to be discussed separately, which was entirely responded to with “no”. This is a drawback, because the information loss linked to this is immense. For various applications the information, whether a tool was replaced or a machine was under maintenance is at least very useful if not critically important.

The survey discussed above shows that in the area of RARR, there is a need to propose a framework to use process data for analytical approaches and to state common mischiefs concerning data storage and data integration. This is why in the following, a framework is presented and common mistakes and lessons learned are presented to address those issues and emphasize the need to deal with the data that is being stored.

The majority of the companies surveyed do not use existing production data to analyze their production process, yet current research in machine learning shows big improvements for several applications mentioned in section 2. Further, LAGAO managed to proof classification results up to 88.4 percent using data-mining methods in 2004. This indicates the usefulness of machine learning methods in the topic of quality prediction and process-failure classification. Moreover, new algorithms in form of deep learning tools, such as convolutional neural networks or long short-term memory cells are used for sequence problems and show great improvements over former algorithms [23,14]. All those improvements contribute to the fact that machine learning bears great potential in RARR and other production engineering sectors, which is underlined by a paper of the *Wissenschaftlichen Gesellschaft für Produktionstechnik* in 2019 [24]. Lastly, referring to a survey of *IDG,* more than 34 percent of the companies mention data quality as the biggest problem for machine learning applications [25]. This is why the following framework is proposed to set a standard for data acquisition in RARR to enable future applications using machine learning.

## 4. Framework

The proposed framework is depicted in Figure 4 and can be divided into three layers visualized by three central grey boxes. The framework should not be seen as the one and only standard but rather as a good example for the forming industry to start working with data analytics.

The first layer of the framework represents every step in the production process of RARR. On this layer raw sensor data is produced. This is an important step, because the sensor data needs to be saved in its raw format, meaning it should not be aggregated, truncated or varied by taking the mean, max or min. Once raw data is transformed in anyway before saving it, the raw dataset is lost even though the raw sample-frequency, aggregation-level or dimension-depth might be needed sometime in the future [26]. By saving raw data, future data analysis is enabled without the exhaustive and time consuming task of providing sufficient data once again. Additionally, the decentralized storage of raw data will be beneficial in a later layer of the framework as well. As for data storage, there are plenty of suggestions for database architectures depending on the type of data. For RARR it is mainly sensor and machine data, which can be stored in a relational database, for example PostGres, SQLITE, MYSQL or time series databases such as InfluxDB and TimescaleDB [27]. A summary of all currently produced data of the production chain can be seen in Table 1 and represents the state of the art in ring rolling. Keeping in mind that there are grown structures in industry and relational databases are the most used [28], it is a considerable trade-off to use an already existing relational database instead of deploying a whole new database architecture. Yet, these data storages should not be used for analysis.

Table 1: Types of data in the RARR production cycle

| Production Step | Structured data | Unstructured data |
|---|---|---|
| Furnace | X | |
| Press | X | |
| RARR | X | |
| Quality inspection | X | X |
| Heat treatment | X | |
| External data | X | X |
| Internal data | X | X |

The actual storage of analytical data is depicted in the second layer. The raw data is then syntactically and semantically transformed by an Extract-Transform-Load-Process in addition to a validation-check. This validation check $f_{val}(x, t)$ checks the sensor data from the raw databases on state and time before transforming them. This step is inspired by a framework proposed by SEJA [29]. Additional external and internal data is also validated and transformed to be stored in non-relational databases such as MongoDB or Cassandra [30]. By adding external data the main dataset from the production chain is enhanced by further metadata. This process is called data enrichment, where the additional data offers further information to the dataset [31]. For example, external data delivered to the company could be metallurgic inspection data or geospatial data from the supplier referring to the blanks origin.

The distributed databases are then managed by a framework such as Apache Spark or similar frameworks to orchestrate all decentralized databases and to manage all necessary steps for the final data integration and preprocessing steps. It also offers potential to be run in the cloud or on a standalone cluster [32]. This hybrid approach makes use of a combination of centralized and decentralized structures and thereby uses all advantages of fog and cloud computing altogether [33].

The third layer is called the analysis layer. To analyze the production data, the only requirement is to connect to either Apache Spark's build in machine learning tools or use the preprocessed data for quality prediction in an external data analysis software.

The simple structure of this framework aids in the process of deploying it into grown structures as well as making troubleshooting a lot easier, because fewer nodes need to be looked at. In addition, the raw data storage can help fixing the framework, because a possible error can be traced back to the raw data causing problems in the $f_{val}(x,t)$ function and thereby the issue can be fixe more quickly. Keeping in mind that some of the requirements today might change, with regards to the upcoming possibilities in research, meaning that the framework has to adapt as well. This task is made easier if the framework is more generalized and simpler rather than it being with a highly specific and restrictive framework.

One thing, especially for the use of machine learning, in fact supervised methods, is, to keep the target that needs to be predicted in mind and always making sure to relate the targets to its data and to store the targets as well. Moreover, it is common practice in many areas to split the storage and computation of such data. In addition, the framework and analysis should also be split up as shown by the dark bounding boxes, see Figure 4. This ensures a higher adaptability for a data-driven company to changes in data (-formats), computational hardware and analysis. [26]

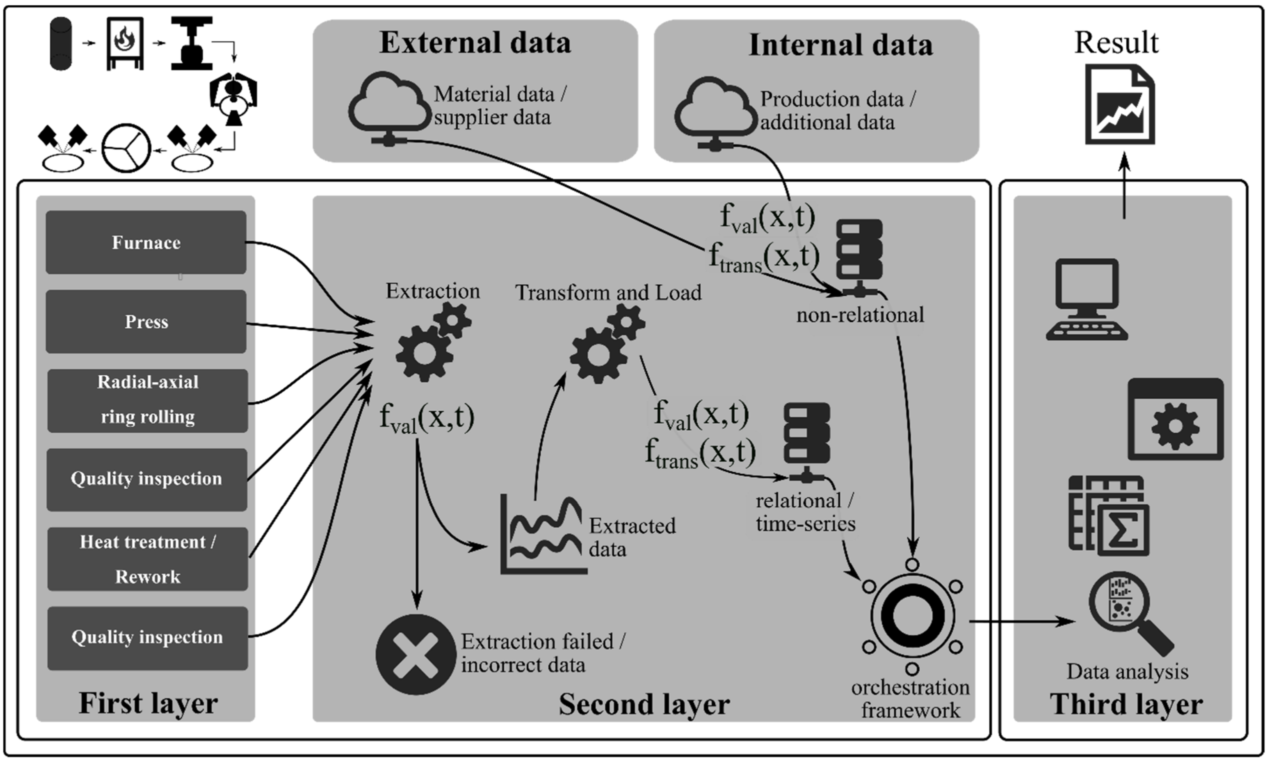


Figure 4: Data-driven framework for data analysis in RARR

## 5. Conclusion and key takeaways

Concluding, the data survey shows that the ring rolling industry already has good prerequisites in terms of produced data. The next step is to make this data available in an analytically useful form and embed this data in a framework as presented above. This should guide a company towards an overall data-driven culture, enabling all kinds of approaches towards data analysis to enhance and optimize present and future industrial applications and production processes.

As key takeaways for the hot forming sector, the following guidelines should be taken into consideration when starting data analysis tasks or establishing a data driven culture inside a company. The key takeaways are summarizations of general proposed guidelines from recent research as well as individually developed best-practices while establishing a data analysis framework in the hot forming sector:

- Data should be saved in its raw-format [29,34],
- Data dimensions should be validated before saving (e.g. frequency, accuracy),
- supervised machine learning methods always need a target related to the data [35],
- timestamps or other identifications should be used[34],
- a standard for measurement units should be set [36],
- a standard for missing values should be set (e.g. "Nan" or "/") [36],
- it is highly recommended to keep up data conformity (throughout the whole company) [24],
- simple is better than complex [37].

## 6. Framework validation

As for a practical implementation the deployment of the proposed framework is currently being put to the test in a company to enable future data analysis. A great challenge is the interoperability with existing structures and undefined standards. The aim is to deploy all key takeaways and the proposed structure in the future.


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