Experiences of a Digital Twin Based Predictive Maintenance Solution for Belt Conveyor Systems

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ABSTRACT

Availability of belt conveyor systems is essential in production and logistic lines to safeguard production and delivery targets to customers. In this paper, experiences from commissioning, validation, and operation of an interactive predictive maintenance solution are reported. The solution and its development is formerly presented in Al-Kahwati et.al. (Al-Kahwati, Saari, Birk, & Atta, 2021), where the principles to derive a digital twin of a typical belt conveyor system comprising component-level degradation models,estimation schemes for the remaining useful life and the degradation rate, and vision-based hazardous object detection.

Furthermore, the validation approach of modifying the belt conveyor and thus exploiting the idler misalignment load (IML) for the degradation predictions for individual components (including long-lasting ones) together with the actionable insights for the decision support is presented and assessed. Moreover, the approach to testing and validation of the object detection and its performance is assessed and presented in the same manner. An overall system assessment is then given and concludes the paper together with lessons learned.

As pilot site for the study a belt conveyor system at LKAB Narvik in northern Norway is used.

1. INTRODUCTION

Conveyor belt systems are of utmost importance in many production lines and are critical in securing the material flow between processing units. Disruption of operation due to unplanned stops when critical component failures occur can lead to unplanned costs and in worst case lead to disrupting the production and delivery to end customer. The systems are used in virtually all process industries, but also sectors where bulk material must be transported. In mining operations, they are found throughout the whole production chain.

These systems are exposed to several hazards that affect their operation and component life. Especially in the mining and haulage sector, the components degrade relatively fast compared to indoor process industries due to harsh environments such as dust, humidity, and excessive loading. In cold environments, bulk material often freezes into big blocks, and fine material can clump together due to the humid environment. There is a risk of steel plates supporting silos to get loose due to numerous collisions and ripping the rubber belt.

Condition monitoring solutions have been proposed since a long time to monitor components and their degradation and strategies on addressing these issue in a maintenance context have been suggested in (Lodewijks, 2004) and (Lodewijks & Ottjes, 2005). A difficulty in the monitoring of such systems is their distribution over a large geographic space and the sheer large number of components which are usually not equipped with sensors. In (Lodewijks, Li, Pang, & Jiang, 2016), a solution is proposed using an IoT approach with intelligent rollers. But the exchange rate of rollers in a belt conveyor system is high which means smart or intelligent versions of rollers need to be replaced and registered appropriately in an asset management registry, posing a challenge on the maintenance and IT organization. Assuming these challenges can be solved, component-level predictive maintenance would be enabled as discussed in (Liu, Pang, Lodewijks, & He, 2018) and (Liu, Pei, Lodewijks, & Zhao, 2019).

In process industries, the roll-out of component-level strategies is still in its infancy and the organizational challenges associated with it need to be first overcome. That being the case, Al-Kahwati et. al. (Al-Kahwati et al., 2021) have proposed a hybrid approach to provide a component-level condition monitoring solution which does not rely on smart or

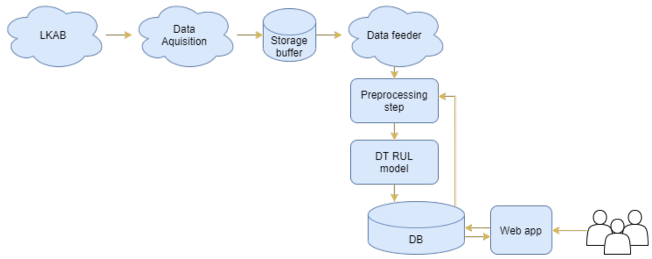

Figure 1. Simplified software architecture for the component condition monitoring model.

intelligent rollers, but is ready for such components. The solution is based on a digital twin of a belt conveyor system, extracted from CAD drawings and adjusted using field observation, comprising degradation models to quantify the component-level estimation of the remaining useful life and rate of change of the component condition. The digital twin makes use of sensor and actuator signals from the control system and static data experimental campaigns, and is realized as Software as a Service (SaaS) on a cloud-based architecture that directly integrates with the IT systems of the asset sites. Adding to this, an extension to the system is developed and commissioned, comprising of a vision based object detection system that is realised as an edge solution on the asset site.

The digital twin and the degradation modeling approach are tested and validated for a period of three months with modifications made to the belt conveyor to exploit the IML for a faster degradation rate of selected components. In addition to this, the accompanying object detection system is evaluated and validated during the same period of time. Adding to this, an approach of placing objects on the belt itself during life operation is employed for a faster evaluation and retuning of the detection scheme. Using the experiences collected from the field, it will be discussed how commissioning and validation of the digital twin are affected by inaccuracies in drawings in relation to the built conveyor (as-designed in contrast to as-built) and how the accuracy in reporting of maintenance actions on the decision support provided by such a solution. Moreover, how the prediction quality provided by the digital twin is affected. Some mitigation approaches for these negative effects are suggested. Furthermore, the validation approach of modifying the belt conveyor and thus exploiting IML for the degradation predictions for individual components (including long-lasting ones) together with the actionable insights for the decision support is presented and assessed based on the experiments conducted on a pilot site at LKAB Narvik in northern Norway.

2. System setup

2.1. UI/UX

The component degradation model does not require new sensor installations other than those already present in the plant.

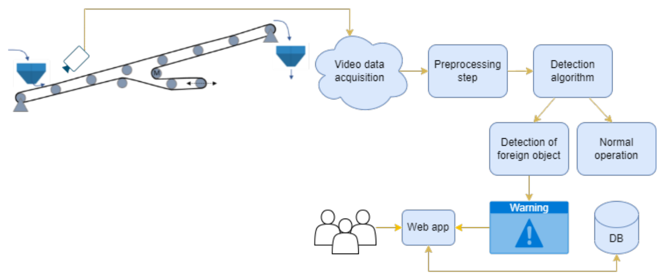

Figure 2. Software architecture for the vision-based object detection. All steps before and including the warning are done on the asset site, via the edge solution.

It is integrated with the IT infrastructure of the site and makes use of sensors readings used in the SCADA, DCS and maintenance systems. The object detection system however needs at least a camera installation if there is none present. An edge computer solution is not required but was chosen to reduce the need and risks of streaming data outside of the plant.

2.2. Component condition monitoring

The digital twin needs to be properly calibrated to the real life belt conveyor system. Information needed for capturing the dynamics and calibrating the model can be found in documents such as the function description, product information documents and CAD drawings provided by the belt conveyor system provider. In addition, the component information and data sheets from various component suppliers are needed.

Figure 1 shows a simplified version of the software architecture for the reader. Data tags from the asset site are needed to form the model for calculating the degradation of remaining useful life. The minimum requirement of data tags for the condition monitoring of the solution are the feed rate, belt speed and the belt tension as described in (Al-Kahwati et al., 2021). The data points are provided to the online cloud solution through a data lake. To have the data points available for provisioning, the tags are transferred to the data lake from the control systems.

The data lake comprises a data compression which is based on signal variation properties, like deviation from the latest registered data point. The minimum deviations needs to be properly adjusted to sufficiently register data points for replicating the system dynamics, while not reacting on noise or random behaviour. Clearly, the data can not be used for in depth data analysis on the sensor behaviour, noise properties and small signal behaviour.

Tags are posted from the data lake via a REST API to a container at Predge. The measurements are then merged into a single file which is moved for further processing and the individual measurements are backed up. When the application is ready, a data feeder will pick up the file and further process

Figure 3. Side view menu of dashboard and belt status overview. The idlers are sectioned appropriately to prevent from cluttering. Each section contains 50 idler sets, that is left, center, right roller each.

it, extracting features to determine the forces acting on the rollers through the degradation model. The remaining useful life (RUL) for each component is updated and operators can view the status of in the web application by clicking the status overview, which is shown in Figure 3.

2.3. Edge solution for object detection

Setup for the vision based object detection system is straightforward. The camera is connected and powered through an RJ45 ethernet cable and allow for using common ethernet protocols. The camera used at the asset site is a FLIR AX8 and comes with a built in light system, however depending on the current light conditions and distance to the belt, an extra light source is recommended and was used at the belt conveyor in question.

Figure 2 shows a simplified version of the software architecture of the object detection scheme. The Object detector is set up by using a computer server box set up at the asset site and captures data from a PoE camera streaming video to the local network. An AI solution for object detection is deployed as a docker container to the server box. When detections are made, the detection frames are saved and presented under the ”object detection” tab in the side view menu. There the operation personnel can review all detections and mark them as false positive should the detection not be related to any object. In other words, the frames get labelled and can thus be reused for tuning or relearning purposes of detection models.

3. Decision making in condition-based and predictive maintenance

The purpose of the application and its development is to help users plan their maintenance actions based on estimations in the RUL model and detections that the object detector has made. Figure 3 shows the current status of the belt conveyor system. The carrying side of the belt is sectioned into 11 sections, containing 50 idler sets each. The colour of the section represents the worst performing roller in the section. Thresholds are set as follows:

- Green: RUL above 4000h
- Yellow: RUL between 2000-4000h
- Red: RUL below 2000h

The values are chosen to fit into current maintenance practices and to enable the user to plan ahead.

3.1. Test cases

In the proposal of the project, several KPIs were defined to assess the validity of the solution models and to provide a preliminary performance guideline for commercial use. The KPIs needed to be translated to a specification and test cases with criteria for the assessment of the test case.

Test case 1: Life operation. Roller failures may not stop the conveyor for long but they create several unwanted stops which could be avoided if the solution can predict such failures ahead of time, thus helping to make better planned stops that will not hamper the production negatively. The first test helps to assess the availability of the solution. The solution needs to be in life operation for at least three months. Within these three months, the availability of the application will be monitored, for the test to pass, there is no room for downtime should the model miss processing measurements from the data lake.

Assessment 1: The test was conducted during a validation period as an operational application. The application was fully operational and hosted on cloud servers. The nature of processing measurements are in batch and uses an intended delay while always backing up processed measurements. This set up brings some sort of protection against outages should either the data lake or cloud servers become inaccessible for some period of time. The system was operational during the whole validation period with automatic restarts upon unforseen errors or outages.
Conclusion: Successfully completed.

Test case 2: Unwanted unclassified object on belt. Unwanted objects that could abruptly stop the conveyor need to be seen early so that the conveyor can be stopped and the objects removed. Different objects other than iron ore pellets will be placed on the belt at least five times. The solution must be able to at least detects 4 of these objects, thus giving an 80

Assessment 2: During the validation period, tests were performed by placing foreign objects on the belt. A total of 22 objects were placed on the belt. Out of these, 19 objects were successfully detected during the tests. Objects missed were darker in colour or thin in shape and blended in with the bulk material which may pose a difficulty since the solution is camera based. Naturally, the solution has successfully detected objects such as big rocks and lumps of material during the validation period. *Conclusion Successfully completed.*

Test case 3: False positive detection of objects on belt. To be able to perform this test, the solution must run for a year. During this time the solution will be monitored to see how many detections are made, and evaluated how many of these were false positive detections. The evaluation is done either by manually inspecting the frames together with operator personnel, or checking inspection logs. The test should pass with a false positive rate of two per week.

Assessment 3: For this end the belt monitoring system was used as a guidance which can generate less than two false positives per week in average. The solution has not ran for a year, thus validation period lasted for approximately six months. During this period of time the number of false positive detections were 962 frames in total. After re-tuning of the algorithm the false positive of the algorithm is down to 143 for the period. This is still more than the anticipated 52 false detections for a 6 month period. It needs to be noted that the data availability for learning true positives and false positives was very limited and longer operational periods are of help here. The tendency is well towards achieving the false positive rate. *Conclusion: Not completed yet.*

Test case 4: Unwanted large objects on belt. At the test site, unwanted large objects on the belt are rare but have the highest consequence level meaning they pose the risk of halting the whole operations when occuring. Like test case 02, all the video streams for the small and big objects placed on the conveyor belt will be saved for fine tuning of the algorithm.

Assessment 4: In test case 2 and 4, the sizes where split evenly among the 22 objects placed meaning 11 were large and 11 small. The system missed three out of these objects and the deciding factor was more the coloring and how slim the object appeared to be on the actual belt, rather than the actual size. Dark objects and very slim objects, for instance a brown cardboard cane blended in with the pellets. Nevertheless, the cane can be classified as a small object whereas the other two missed were large dark-colored cardboard cutouts. *Conclusion: Successfully completed.*

Test case 5: Prediction of component failure. This test case is connected to the components with priority 1, namely the roller components. In order to perform this test, data is aggregated from the data lake and run through the condition monitoring solution, and the indications for upcoming failures are collected. A comparison with maintenance and inspection protocols for the same time period is made. Then a classification of the predictions as true or false positive is made. This test has passed when 80% of the maintenance and inspection data are predicted in good time.

Assessment 5: In test case 5 there was a problem of not knowing the RUL of components beforehand. Maintenance logs only contained information about rollers being exchanged, but not specifically which roller. Usually in the test plant there is approximately exchanges of 10% of the total rollers, which means that the rollers exhibit an operational life which exceeds the validation period. Moreover, maintenance data could not be used for validation purposes, which is important to consider in the lessons learned. This also meant that the amount of maintenance data can not be considered in quantification.

To assess the test case a specific experiment was conducted where two newly installed idler sets were raise vertically by 70mm, to speed up the degradation process due to increased IML which results in higher friction and downward force from the belt weight on the idler (CEMA, 1997). It was difficult to foresee if the degradation model would fit for such an abnormal geometric change and also what the life expectancy for a roller would be in real life. This modification was also reflected in the model to see if it could predict an early failure.

For the decision support on the prediction of an upcoming failure, thresholds for RUL and RoC were defined. The achievement of the threshold would then trigger a highlighting of the roller in the web app. The RoC was very high, and RUL was immediately reducing immensely and in real life the rollers failed very rapidly. One of the rollers failed already after one day. The decision support would indicate the rollers properly, but it is difficult to understand if the degradation model is capable to reflect such abnormal behaviour. *Conclusion: The test case needed to be modified. Modified test case completed successfully. Remaining question marks due to lack of realism in the modified test case.*

Test case 6: Increased availability. Preferably the value creation is quantified prior to commissioning, but in case of the proposed belt conveyor condition monitoring solution, an organizational change is needed to follow up the roller exchanges accurately. If the roller exchanges are not followed up in detail, the performance of the indications is negatively affected and the availability can not be quantified correctly. To conclude, this test case is not feasible and can not be performed. It was therefore decided to discontinue test case 6.

4. Deployment and Operation

The solution is a SaaS solution which means there is no software installation at the site. Instead, the solution need to be integrated with the IT infrastructure of the asset, namely their data lake. The integration uses standard APIs. Furthermore, the asset site need to make the SCADA, DCS and maintenance system data available in the data lake as specific tags that can be exported to the SaaS solution.

During inspection, maintenance and evaluation, the operator personnel is able to interact with the system through a webapp interface. After login, the user is presented with an interactive dashboard of the system as shown to the right in Fig. 3, and tables presenting components that are either deviating or have low predicted remaining useful life. Both systems, namely the model for component condition are deployed separately and store results in the same manner. Nevertheless, they are presented as the same SaaS and can independently be shut off for modularity should future customers not be in need of either one. The app allows operators to interact with the model. It loads current condition data calculated by the degradation model from the database and presents in on the dashboard. Figure 2 shows the software architecture of the setup. The dashboard shows the belt conveyor, with sections coloured in a traffic light scheme depending on the status of components within section along with aformentioned lists ranking components by deviations or RUL.

In the side view bar as shown in Fig 3, forms are present for the user to fill out exchange or deviation data. The forms interact with the system in the manner to either reset RUL of components (exchanging components) or by listing them as deviations that need further inspection. Furthermore, detections from object detector are shown as a list the possibility for the user to mark detections as ”False positive” should the detection not be correct. The forms are thus used as a feedback to the system with ground truth information.

4.1. Component condition monitoring

Since the digital twin of the plant system is run in parallel with the belt conveyor, there is no initialization criteria for the system, other than initial calibration described in section 2.1. Considering the conveyor contains rotating components in the thousands, information regarding the installation date and maintenance actions on specific components such as rollers are rather sparse. This was the case with the asset in question and consequently the rollers were initialized to 50% RUL, and were reset to 100% once maintenance actions are taken. The digital twin model is created in Python and deployed as a Docker container to a cloud cluster for operation. The model acts on incoming data, calculates the degradation of remaining useful for each affected rotating component and updates individual records for the components in a database. A rough software architecture for the model can be seen in Fig 1. The maintenance actions are noted through forms in the web app and is coupled to the database for the digital twin. Exchange actions resets the component on the DT level of the figure.

4.2. Edge solution for object detection

Contrary to the component condition monitoring, this solution suggests, hardware installations on the site. Namely the at least camera and the light sources with respectively cabling. The solution further suggests an edge server solution at the site but is not a limiting factor. For commissioning, the following step wise approach needs to be realised:

1. Select a strategic position of the installation of the camera and light source:

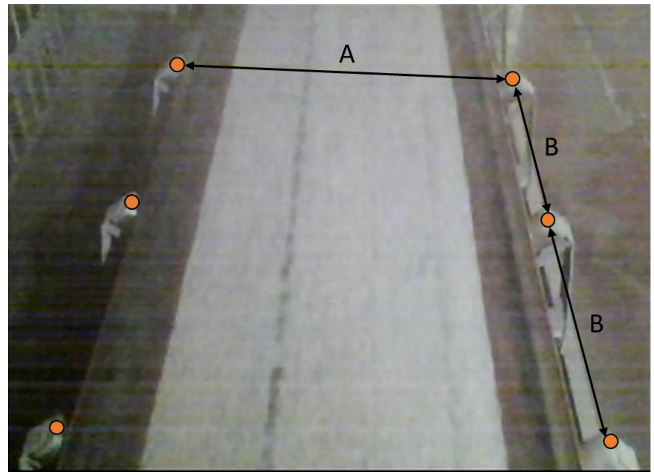

Figure 4. Drawing to indicate the needed measurements for the calibration.

   (a) Free field of view on the belt covering a length of 3.6m.
   (b) No additional feeders downstream.
   (c) Facing the incoming direction.
   (d) Stable light conditions (limited number of commuting vehicles with head lights).
   (e) Sufficient downstream distance to enable a full stop of the conveyor should dangerous objects be detected.
2. Installation of the camera and light sources.
3. Enabling data stream, preferably RTSP and making the camera available on LAN.
4. Installing edge server on site **if needed** and make it available on LAN and accessible remotely.
5. Initiate operation of detection system for acquisition of training data. Exercise specific experiments with manually added objects for faster training and tuning.
6. Proceed to validation and continuous operation for the solution.

Estimation of object sizes depends on the camera distance to the belt, its zoom and angle to the belt. Calibrating the size estimation requires some measurements on the conveyor at the installation site, as show in Fig4. The camera view of the belt should be so that the top three idlers are completely visible. These are indicated by the orange dots in the figure. Moreover, the measurements **A** and **B** are necessary and can be taken directly from construction drawings or measured on site.

5. Experiences

The test cases have been completed except for test case 3 since the application has not been in operation for the required time. The test case is not tied to any KPI but worth mentioning is that tuning of the algorithm is an ongoing process to reduce the number of false positive detections and have a reliable as possible solution that is deemed trustworthy by the operator personnel.

The solution has been in life operation for more than 6 months. Naturally, cloud applications like any other require restarting when errors that were not intended for arise. Such errors may arise due to corrupt data or even power outages along the chain of the system architecture shown in Figs 1 and 2. Since the digital twin model of the plant always backs up streamed data from the asset data lake, it has the possibility of reprocessing measurements up until current time, the model does virtually not experience any down time. The object detector, even though it automatically restarts on errors and power outages, is affected by this since it streams live data. Nevertheless, the restarts require seconds of downtime and the same can be said for the web application. The system is judged to have well met the requirement of availability.

The system performs object detection of unwanted and unclassified with a high degree of precision. As mentioned in previous section, test cases 3 and 4 were conducted by placing objects on the belt. The detection rate of these tests were 86.3%, and beyond that, the system has made 240 detections of unwanted objects such as big lumps, rocks, slabs of concrete.

Prediction of component failure point in the right direction, but more validation is needed since the system has not tracked any component during its whole lifespan except for the two idler sets purposely installed with a vertical misalignment in test 5 to get a faster degradation rate. One roller failed at the 20-day mark and the other failed after only two days. The model predicted failures within 17 and 30 days respectively. The conclusion from these experiments is that since the model seems fairly accurate since it could predict such a large reduction in RUL from the new operating characteristics, although with some uncertainties for the experiment.

Regarding if the system provides increased availability, the project group is positive that this can be achieved using the system although not possible to establish quantifiable understanding during the project runtime. Current maintenance practices does not manage or track individual rollers/idlers and the maintenance system does not offer a means of managing them. As a result, downtime could not be properly established for either baseline and validation. Rollers being exchanged during the project were not reported as intended and benchmarking subsequently not possible.

5.1. Lessons learned

The project set out with the ambitious goal of raising the TRL of a prototype solution for condition monitoring of belt conveyor systems to 9 which is a market ready solution with validated performance characteristics. During the project, several challenges were encountered that were not foreseen and are obviously vital for later efforts. Those will be discussed in the following.

5.1.1. Maintenance practice in conflict with validation

Current maintenance practices might prevent the establishment of a baseline or the benchmarking of a new technology. It is therefore vital to assess current practices, data acquisition and data quality early on during the specification phase to make sure that there is sufficient high-quality data available for the test and validation strategies of the new technology. Furthermore, the validation should consider maintenance practices with respect to the degree of changes that are necessary to implement. Too many changes will induce delays and a higher amount of commitment and engagement of maintenance personnel and operators, which can conflict with the amount of time and resources planned in the project.

5.1.2. Covid-19 related delays and accessibility

Access to pilot and demonstration sites can be restricted and induce delays for the implementation, commissioning, and on-site activities. Validation plans need to consider a certain degree of flexibility and backup plans due to the currently ongoing pandemic. The complete project has been affected by this issue.

5.1.3. Real life ambient conditions

Real life ambient conditions may differ from the theoretical development of the solution and the foreseen real life behavior. Such factors are difficult or impossible to measure. These conditions might also occur during a limited time span and might be hard to foresee. It is important to collect as much information as possible during plant visits due build a good intuition. The validation can then use the collected knowledge and make decisions on abnormal behavior and/or the need to exclude them from validation.

5.2. Normal operation supersedes experimentation

Execution of planned tests in normal operation is difficult as modifications that affect operations impose a risk that could in the worst case render stops. Such as adding unwanted objects to a material stream. Normal operation will therefore supersede experimentation and tests cases can thus be delayed. While this is not unknown news, it may be overlooked during test case planning.

6. Conclusion

The assessment of the test cases performed shows promising performance characteristics for the system in using it as a decision and maintenance support tool. Used per guidelines, the solution keeps track of and predicts the future status of individual components such as rollers and pulleys within a belt conveyor system. Moreover, the solution can detect unwanted objects on the belt, imposing a hazard for the belt life. The object detector shows high detection capabilities and relatively low false positive rates during the tests.

It further shows that the solutions can predict roller failures using given thresholds, and the object detector fulfills the true positive detection requirement. Principally, improvements are needed on the false positive rate which is is exceeding a threshold taken from current performance of a belt monitoring system. As for the desired increase in availability, the lack of data needed to assess a baseline level and current maintenance practices leaves impossible to express or measure. In general, it can be concluded that the developed solution is commercially viable for implementation and value creation.

The authors thus recommend:

1. **Early on involvement from operators.** For testing and commissioning of the solution since their insights on smooth operation and possible earlier use of decision support tools aids in tailoring the UI/UX to the customer. This would also be a natural step in training and supporting different roles at the site.
2. **Object warning.** A lot of hauling sites have cameras that stream live data to operators in control rooms for manual inspection. These systems usually back up video during a set period of time. Generating a timestamp that could be sent via TCP from the object detector to this system for video replay in the control room can be used as an intermediate step towards automatic conveyor stops from a detection. It enables an automated labelling of frames from the action operators take (Stopping/not stopping belt).
3. **Hand-held devices.** The accuracy of reporting component exchanges is vital for the system performance. Using hand held devices in the field would enable the direct reporting of component exchanges without relying on secondary note-taking. It seems less likely to miss a report action and reduces effort.

Finally, it should also be noted that the excellent collaboration of the project participants during the given corona situation made the successful completion of the project possible. While less time was spent on travel to and from the site, it created an overhead in online meeting and more efforts by the local project participants.

ACKNOWLEDGMENT

Funding received under grant number 15099 from EIT RawMaterials (in turn funded by the Framework program Horizon Europe of the European Commission) is hereby gratefully acknowledged. The authors would also like to thank LKAB Narvik for the great support cooperation throughout the project.

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BIOGRAPHIES

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