International Journal of Current Science Research and Review

ISSN: 2581-8341

Volume 03 Issue 01 January 2020

IJCSRR @ 2020

Predictive Maintenance Solution for Logistics Robotic Cell

Claudiu Ioan Abrudan[1], Paul Emanuel Baru[2], Florin Bugnar[3]

[1]Accesa IT Consulting

[2]Fit for Business

[3]Interglobalis Consulting

ABSTRACT

The Industry 4.0 trend is known as being the next industrial revolution. The major change introduced by this concept, is the digitalization of the industry. The manufacturing field that has been already transformed into automation (being considered as the third industrial revolution) need to be connected, to be gathered data based on witch new business value is expected. The logistic domain suffered also a lot of change along the last years. Robotic cells are deserving logistic chains and maximizes the outcome. Together with the use of robotic cells, machines are used as a service, in which they are being paid as much as they produce. Robots cells as a service, in the word of selling everything as a service. For this business model, predictive maintenance is an important aspect, since a not working cell, can't generate value and revenue. Current research approaches the predictive maintenance solution for logistic robotic cell, in order to increase the uptime of the machine, and therefore the output. Logistic machine producers sell the cells as a service and assumes all the risks that appear.

KEY WORDS: predictive maintenance, robotic cell, machine as a service, uptime, palletizing system

INTRODUCTION

No matter which production sector wear are speaking about, technological innovation is essential for each successful business. The industry 4.0 trend represents the 4th industrial revolution and defining new industry standards. The standards are not approaching risk or safety aspects, but productivity and business competitiveness. Smart factories are replacing the traditional ones and integrate all old software solution and connects the machines with each other. The digital twin of the production system is operated by engineers in their offices thanks to the internet of things, big data and data engineering solutions that gather the real time parameters and brings the digital twin to life.

Adapting the whole production cycle to the digital industrial revolution doesn't give only a competitive advantage, but keeps the producer alive, in a world where slowly all the components are moving in the same direction. Not keeping up the peace, would mean the loss of business and disappearance from the market. Since mechanical parts of the production process reached almost their maximum development, the single part where things can be improved, are the real-time monitoring and optimization of the machines and production flows. The digitalization of the production brings the manufacturers in a highly competitive zone where factories are connected and autonomous. The output is:

- Less time needed for manufacturing products;
- Decrease of costs of the production;
- Increase of customizability of the products.

All these aspects give conduct to higher profits. For this, there is the need of understanding the new business model and the actions that need to be taken in order to achieve the new approach, aligned to the Industry 4.0 principles. The new technologies that brings the success, are the following:

- IoT – Internet of Things means installing sensors or similar hardware/devices, that read the status of the system and generates data that is being transferred in order to be processed;
- Cloud – A modern data lake and databases where the data is structures and prepared for other systems to be interpreted and analyzed.
- Data science – Building advanced algorithms that processes the data (generally large amount of data) with the scope of identifying a defined state of the system. Generally, such an algorithm is also known as artificial intelligence and has the power of proposing solutions based on similar situations appeared in the past;

- Data analytics –reports and dashboards based on witch the human can take in less time, the best decisions.

The current research approaches a worldwide logistic equipment producer that is producing various types of machines, but the most advanced ones are the robot cells, for palletizing boxes on pallets. The robotic cells are being sold, beginning 2016 as a service, and therefore the uptime of these machines is vital. A functioning machine generates value and therefore the return of investment for the producer. The components of such a robotic palletizing cell are presented in figure 1, below.

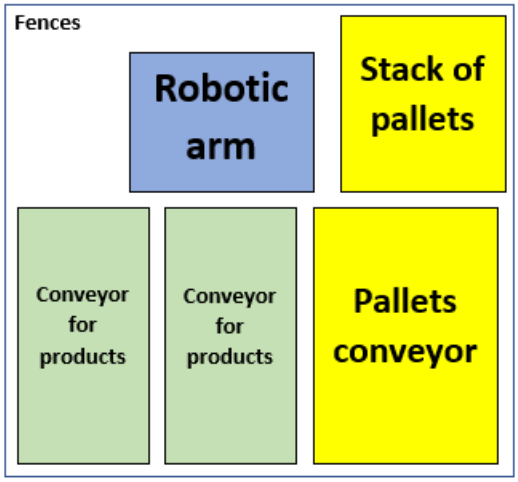

Figure 1. Components of a logistic palletizing cell

As illustrated in the figure, the robotic cell is composed of a robotic arm, a stack for pallets and a set of conveyors that are deserving the cell: for products and for the loaded pallets.

PREDICTIVE MAINTENANCE APPROCH

Each part of the system can suffer damages or problems, therefore, thanks to the industry 4.0 principles, a predictive maintenance solution was developed and implemented so that the producer gets the smallest downtime.

ROBOTIC ARM

The robotic arm is one of the key components of the palletizing cell. In order to create a predictive solution for this, wehave to make sure that all the possible failure reasons of the robot are monitored and predicted. The robotic arm comes with a preset software that measures constantly the quality of the movement: speed, accuracy and other aspects that indicates a damage or a mis functionality.

Additional to this, in the IoT direction, we added for the research also:

- vibration sensors on the key positions of the arm – that will identify the breakdown of mechanical parts, that will generate additional vibrations, different form the normal operation;
- and a video camera that observes any change in the moves and appearance of any other unwanted movements or events.

The data is being gathered and sent into the cloud to a centralized storage.At the setup of the cell, normal data is being defined, this means data generated during the normal/optimal operation of the component. This data is considered as reference data, or training data. After the setup of the robot, the normal operation generates data that is analyses in real-time and compared with the training data. If any other parameter is outside a defined threshold, a notification is being sent that a damage will follow. One step further, after some appearance of some damages, there can be created a damage library correlated with the appearance of some parameters before. The analysis and notifications will be sent to a central software solution, that will be presented later. There can appear damages in the mechanical parts, electrical motors or at the electronic parts of the robotic arm.

Of course, the robotic arms come with a maintenance plan, that needs to be respected. Our defined predictive maintenance is on top of the plan and creates additional recommendations to avoid downtime.

CONVEYOR FOR PRODUCT

The two conveyors for the products are used for bringing the boxes of products into the robotic cell, so that the robotic arm can place them on the pallet. The most components of the conveyor are mechanical, some additional electrical (optical barriers,

motion sensors) and pneumatical for actioning elements and components. There is no maintenance plan scheduled for motors and electrical parts, but all the others have no maintenance plan.

In this situation, for predicting problems, that were installed:

- vibration sensors, that measures in real-time the possible occurrence of problems. If any mechanical part gets broken, we can easily identify the problem, by measuring the vibrations;
- Additional to this, we gathered data from the motors. If the power consumption the motors indicates if the operation is normal or something different appeared.

Data is gathered and sent into the cloud. The real-time data is always compared with the set of training data, generated during a normal use. Thresholds are defined, and, if any parameter is deviated from the normal, notification is sent, and reports are appearing in the dashboard of the centralized software solution.

CONVEYOR FOR PALLETS

The conveyor for the pallets has the same components as the conveyor for the products but is designed to stack the pallets and prepare them to be loaded. As soon as a pallet is fully loaded, it can be sent outside the cell. The components are mostly mechanical, but also few electrical and pneumatical. The predictive solution mounted here is the same as before, vibration sensors for identifying any anomalies in the operation. Data is being analyzed in real-time and compared with the training data. As soon as a change is identified, there is generated a notification and a report in the dashboard.

PALLETS STACKER

This component is one of the less used components of the cell but having an important meaning. The empty pallets are stacked here and one by one prepared to be loaded. The most stackers are actioned using pneumatical system, so that less damage or breakdowns appear. We decided here to monitor this component of the robotic cell with a video camera, that is also monitoring the conveyor for products. So, no additional IoT components were installed for this component.

ENTIRE ROBOTIC CELL

The robot cell has an entire plan for maintenance for the motors, electrical parts and mechanical parts. This should happen after a certain period of operation. This prevents unexpected breakdowns and is generally recommended by the suppliers so each component of the cell. Since the factory aggregates all the components, the defined predictive maintenance solution was built on top of the recommendations in order to:

- Predict failures outside the maintenance plan;
- Have a longer operation time, over the maintenance plan, if the components aren't presenting failure signs. Therefore, the return of investment is accelerated, since the downtime is minimized. After the recommended time of maintenance is reached, and there aren't any maintenance actions, the thresholds of the algorithms decrease, so that the sensibility of the system increases.

All the gathered data from the external additional mounted sensors and video cameras is being sent into the cloud and analyses in real-time thanks to some alogisms that learn form the real operation of the cell. This algorithm can be technically defining as machine learning and artificial intelligence on big data.

The central predictive maintenance solution is installed at the robotic cell producer side that can monitor in real-time the operation of the client's cell. If notifications are appearing, the producer sends immediately a maintenance team with the needed spare parts so that the change is being made before the breakdown appears. The only mandatory condition is the connection of the cell with the cloud, so that real-time data is sent. On the hardware part, the hardware does a lot of processing on the edge, so that in the cloud, the sent data is the minimum meaningful data. Sensors generate terabytes of data daily and uploaded in the cloud hundreds of megabytes.

CONCLUSIONS

The Industry 4.0 solutions are meant to generate new revenue streams and optimize the operation of the manufacturing systems. In order to achieve this, step by step each component of the manufacturing system need to have digital capabilities. Logistic robotic cells are one of the most advanced solutions in the logistic domain. These cells automize logistic aspects and get significant results. Since the market is very mature, the logistics machine producers, started to concentrate on selling their solution as a

service. The revenue stream is constant and more efficient, from the point of view of the producer, but the risk is taken on the producer side, and therefore, a lot of optimizations need to be taken.

Predictive maintenance solution is one of the business outcomes of the Industry 4.0. Based on data, generated by the sensors and devices installed in the factories, and thank to a real-time analysis generally possible thank to the availability of the data in the cloud, predictions are made so that downtime is avoided.

Figure 2. Real time analysis of the gathered data, with the given threshold

The predictive maintenance solution is based onanalyzed data and correlated with then regular maintenance plan of each machine. For the current research there was build a centralized solution that gathers the parameters from the sensors, analyzes them and displays them on dashboards. If something occurs, the maintenance team is ready to replace the exact spare part needed and, in less time, before the actual breakdown is happening. This generates an insurance for the customer that the installed system is always up and running.

REFERENCES

1. Ahmad, A., Maynard, S. B., & Park, S., Information security strategies: Towards an organizational multi-strategy perspective. Journal of Intelligent Manufacturing, 2014
2. Arab, A., Ismail, N., & Lee, L. S., Maintenance scheduling incorporation dynamics of production system and real-time information from workstations. Journal of Intelligent Manufacturing, 2013
3. Bellifemine, F., Caire, G., Poggi, A., &Rimassa, G., A software framework for developing multi-agent applications, lessons learned. Information and Software Technology, 2008
4. Peng, Y., Dong, M., &Zuo, M. J., Current status of machine prognostics in condition-based maintenance: A review. International Journal of Advanced Manufacturing Technology, 2010
5. K. P and A. S. P, Intelligent Healthcare Monitoring in IoT, Int. J. Adv. Eng. Manag. Sci., 2018
6. W. A. Jabbar, M. H. Alsibai, N. S. S. Amran, and S. K. Mahayadin, “Automation System for Smart Home, 2018.
7. J. Shekhar, D. Zerihun, and M. Haile Abebe, “Automated Classroom Monitoring with IoT and Virtuino App,” Int. J. Adv. Res. IT Eng.2019.
8. S. Bhowmick, B. Biswas, M. Biswas, A. Dey, S. Roy, and S. K. Sarkar, “Application of IoT-Enabled Smart Agriculture in Vertical Farming Sutanni,” Adv. Commun. Devices Netw., 2019
9. PLX-DAQ | Parallax Inc., https://www.parallax.com/downloads/plx-daq, 2019
10. Abrudan, C., I., Chiș, A., I., Marian, L., Abrudan, I.,Transition Costs in the Flexible Manufacturing Systems, RMEE2010 International Management Conference, 2010

11. Abrudan, C., I., Marian, L., Chis, I., A., Optimal scheduling of a flexible manufacturing system according to the restrictions of the market demand (Game Theory Model), RMEE2011 International Management Conference, 2011
12. Abrudan, C., I. , Marian, L. , I. Abrudan, Calculation Model for Obtaining Competitive Parameters in the Flexible Manufacturing, 7th International Conference „Management of Technological Changes", 2011
13. B. Johansson, R. Kacker, R. Kessel, C. McLean, R. Sriram, Utilizing combinatorial testing on discrete event simulation models for sustainable manufacturing, Proceedings of the ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, 2010
14. J. Pope, A. Bond, A. Morrison-Saunders, 2015, A conceptual framework for sustainability assessment, A. Morrison-Saunders, J. Pope, A. Bond (Eds.), Handbook of sustainability assessment, Edward Elgar, 2015
15. C.I. Abrudan, P.E.Baru, R.Lungu, Applying Scrum Methodology into the Production Processes of a Logistic Equipment Producer, International Journal of Current Science Research and Review, 2019
16. Liu Q, Dong M, Peng Y. A dynamic predictive maintenance modelconsidering spare parts inventory based on the hidden semi-Markov model.Proc Inst Mech Eng Part C J Mech Eng Sci., 2013
17. Paprocka I, Skołud B. A hybrid multi-objective immune algorithm for predictive and reactive scheduling. J Sched. 2017
18. Prytz R, Nowaczyk S, Rögnvaldsson T, Byttner S. Predicting the need forvehicle compressor repairs using maintenance records and logged vehicledata. Eng Appl ArtifIntell., 2015
19. Baptista M, Sankararaman S, de Medeiros IP, Nascimento C, PrendingerH, Henriques EMP. Forecasting fault events for predictive maintenance using data-driven techniques and ARMA modeling. Comput Ind Eng., 2018
20. R. Sipos, D. Fradkin, F. Moerchen, and Z. Wang,"Log-based predictive maintenance," in Proceedings of the 20thACM SIGKDD international conference on knowledge discovery and data mining, 2014
21. H. Opocenska and M. Hammer, "Use of technical diagnostics in predictive maintenance," in Mechatronics-Mechatronika (ME), 2016