Trash Management System using DL

Dr.Vempati Krishna[1], Dr.B. Sunil Srinivas[1]
[1]Assoc.Prof.
Computer Science and Engineering
TKR College of Engineering & technology vempati.k@gmail.com, sunilsrinivasb@gmail.comHyderabad
T.Rajini,
M.Tech Student
Computer Science and Engineering
TKR College of Engineering & technology rajinithanam13@gmail.com, Hyderabad

Abstract:

Automated machine learning is presented as a viable solution to a real-world issue in Smart Waste Management. This article focuses on the difficulty of detecting an emptying of a recycling container using sensor readings, or binary classification. In a realistic environment, where the vast majority of the occurrences were not true emptyings, a wide variety of data-driven approaches to the issue were explored. Both the current model, which was manually developed, and a modified version of it, as well as more traditional machine learning techniques, were among the strategies explored. With the use of machine learning, the current manually constructed model's classification accuracy and recall were increased to 99.1% and 98.2%, respectively. Based on the filling level at certain intervals, a collection of features were generated and fed into a Random Forest classifier to arrive at this answer. Finally, the top performing solution enhanced the quality of predictions for emptying time of recycling containers in comparison to the baseline existing manually created model.

Keywords—smart waste management, emptying detection, classification algorithms, data mining, automated machine learning, grid search

DOI Number: 10.14704/nq.2022.20.11.NQ66346 **NeuroQuantology 2022; 20(11): 3383-3390**

1. Introduction

Many fields of life and research, including industrial informatics, stand to benefit greatly from advances in machine learning. The automated machine learning (AutoML) method has been developed to speed up the process of applying machine learning to real-world issues. Specifically, it applies the data-driven technique of AutoML to real-world issues that already have workable (model-based) solutions, expanding the scope of the original approach. There are five stages to this method:

• Data collection that may be put to use in the process of developing and assessing potential solutions

• The information gathered is used to assess the current method of dealing with the issue;

• The data-driven optimization and assessment of the current solution's parameters;

For this issue, standard machine learning methods may be used.

If the outcomes of the machine learning algorithms may be enhanced by the inclusion of more features, feature engineering techniques are used to investigate this possibility.

One of the greatest difficulties brought on by the exponential increase in urban populations is trash management, where the technique is applied to a problem. In Europe, for instance, it is estimated that each individual generates six tonnes of garbage each year from common household items. When devising a plan to deal with the problem of waste management, it's important to look in a number of different approaches. Both financial and ecological considerations need to be made when putting these measures into action. Both are heavily impacted by how garbage is transported, so finding ways to improve that process would have a major impact. However, timely emptying of recycling stations is essential if they are to maintain a sanitary environment. With hundreds of recycling stations (perhaps including many containers) spread out across a wide region, it becomes more difficult to meet this criterion. Challenges in optimizing trash transportation may be addressed with the help of a Smart Waste Management system that incorporates aspects of the Internet of Things. The system will enable individual recycling bins to notify their fill status. It is possible to anticipate when a recycling container will need to be emptied thanks to the system's enhanced functionality; this is the point at which the container's fill level will reach a predetermined threshold. Forecasting fill rates will help cut down on unnecessary trips while still meeting the overcapacity stipulation. The effectiveness of a Smart Waste Management system, however, will depend on the accuracy of filling level estimates. The technological hurdles to making reliable forecasts are many. Based on our investigation of a real-world Smart Waste Management system, we know that one of these problems is ensuring that sensor readings from affixed containers accurately reflect when those containers have been emptied. Section II-B demonstrates that accurate detection of emptying is crucial to accurate filling level forecasts. Due to the negative impact of inaccurate detections on filling level predictions, detection of container emptying is a crucial stage in achieving qualitative predictions. For this reason, it employs the offered technique to the emptying detecting issue. Additionally, the research highlights the difficulties and significance of emptying detection for the operation of Smart Waste Management systems for the first time. The Smart Recycling R, a real-world Smart Waste Management system, is taken into consideration. Because precise emptying detection is a necessary condition for precise emptying time prediction, this paper is concerned only with this aspect of the Smart Waste Management system under consideration. It demonstrates how the system currently handles the problem of detecting when a container is empty. It was painstakingly built by hand using subject expertise. It is also well-known that the current manually developed model's poor detection capability is a limiting factor in developing more accurate forecasts of when a container will be emptied. As a result, we suggest a data-driven strategy to enhance the performance of the system's emptying detecting mechanism. A dataset utilized in it was acquired as part of the implementation effort. It offers both a theoretical and practical advance. The aforementioned technique is the main theoretical contribution. Several potential approaches to the emptying detection issue were developed and explored as part of the applied contribution, which relied on the application of methodology to the problem. Solutions that were looked at were.

2. Related Work

Competing commercial solutions use Smart Waste Management's ability to address environmental problems while also embracing elements of Clean technology and the Internet of Things. Both smart containers and retrofitting sensors fall within the category of commercially accessible options. In the form of trash cans and cardboard recycling bins, "smart containers" are equipped with sensors and motors to automatically compress garbage when they reach a certain volume. Customers for these sorts of bins and garbage cans often reside in smaller eateries, industries, and metropolitan regions. Smart containers are used in commercial products like Big Belly and CleanCUBE by Ecube. Some other systems similar to the planned Smart Recycling R system are Enevo, CleanFLEX by Ecube, Sensoneo, Onsense, Smart Waste by Citibrain, and Smart Bin. Since CleanFLEX also predicts when recycling bins will be full, it is the most relevant to Smart Recycling R.

The Smart Waste Management field encompasses the whole scope of a Smart Waste Management system. Due to the fact that recycling bins are usually picked up by vehicles, concerns like fuel efficiency are also closely tied to Smart Waste Management. Related research on the containers, data gathering, and sensing methods is described in the next section. Collecting data in an energy-efficient way [12] where methods may also be taught through data-driven methodologies [13] and concerns relating to a computational infrastructure [14] for supporting functionality of a system are other significant factors for design of such systems. Research into Smart Waste Management now often centers on the Internet of Things as an enabling technology. Numerous studies have proposed employing different technology implementations to aid in the solution of the Smart Waste Management challenge in major cities. It was proposed that heterogeneous devices share data using a platform that is both adaptable and extensible. The purpose of the system was to check how full each trash can was before collecting it. This information might then be shared with other decision-making algorithms to help figure out how many garbage trucks or recycling bins should be stationed in a certain region. The platform was designed for bigger containers than those used by the Smart Recycling R system, which was aimed for smaller household trash cans. A container is a bigger garbage receptacle (2 m3 and more), often collected by huge trucks equipped with a crane, whereas a trash can is used by households and in public places in cities. Similar to the Smart Recycling R system, another paper discusses the need of and potential applications for "Smart Waste Management," and proposes a solution including ultrasonic sensors that upload their level to the cloud for further data processing. However, the paper simply provides a high-level overview of the system and its aims, with no consideration given to emptying detection. Information technology will help in the development of an intelligent and environmentally friendly urban garbage collection system, according to a literature assessment of various analysis and optimisation methodologies for urban solid waste management.

Radio-frequency identification and sonar technologies were found to be of interest in the literature study, and both have been utilized or are employed in the Smart Recycling R system. The Smart Recycling R system has been the subject of two case studies, both of which outlined the system's development process and elaborated on the system's effect on its stakeholders. However, the problem of empty recycling container identification is not emphasized in these case studies since it is a very specialized issue emerging from the selected sensing approaches. The system would not work without it, however. As shown in Fig. 1, for systems with retrofitted sensors, proper emptying detection is essential for permitting accurate filling level predictions. Because choices are grounded on predicted filling levels, the overall efficiency of the Smart Waste Management system is impacted. As a result, figuring out how to determine whether a system is empty is a vital step in the design process. This work is the first effort we are aware of to systematically investigate potential approaches to this issue.

3. Methodology

Thing and Young's Trash Net dataset was used in our research. There are a total of 2527 photos in this collection, which covers six distinct types. The following table breaks down the total number of pictures in each category. Each photo was shot using an iPhone and has a 72 ppi resolution in the original. About 75% of all records were utilized for training purposes, while the remaining 25% were used for research and development. So, we used a total of 1894 photos for our training set and 633 for our test set. Listed below is a breakdown of the total number of photos used in both the training set and the test set. For optimal model performance, we downsized all of the photos we used for training and testing to 227 by 227 pixels.

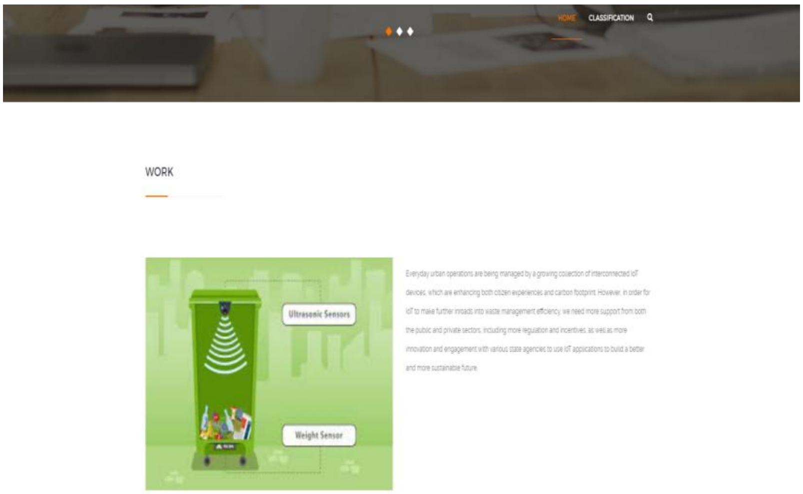
In this study, we investigated and adjusted Transfer Learning Models. We evaluated the three topologies using Softmax activation for the final fully linked layer. Test accuracy was greatest for the updated AlexNet model, and it took little time to train. This motivated us to further investigate the potential of our modified AlexNet architecture, leading us to create two models with differing loss and activation functions in the final fully connected layer. The Adam optimizer with a mini-batch size of 32 was utilized for both models. We also experimented with a dropout rate between the first and second completely linked layers, in addition to the baseline model. We tried a number of different dropout rates but found no discernible difference in model performance, so we settled on the default value of 0.5. We also used the data augmentation methods described in the Datasets section. We were only able to train with data augmentation for a total of 30 epochs due to limitations in our computational resources. Accordingly, we used a partial data augmentation strategy, in which we first trained the model with data augmentation for 30 epochs before switching to training it without data augmentation for another 30 epochs. How each model converged determined both its learning rate and its decay timeline [18].

While testing out several schedules for the learning rate, we discovered that a rate of 0.000005 was sufficient for the majority of our models. With dropout, we only employed a learning rate of 0.00001 and a decay rate of 0.00000025 for the first 20 epochs since it considerably slowed down model convergence. Our training duration was also affected by the model's convergence behavior in terms of the number of epochs. In this study, we use loss functions to assess the efficacy of our training models. The loss function is the function used to calculate the deviation from the desired values in the algorithm's outputs. As the model's accuracy decreases, this function's value increases. This may be determined by contrasting the two datasets used during training and testing. The loss function should be minimized in all algorithms and particularly in this one. It is assumed that the loss function is at zero under normal circumstances. The cross-entropy classification loss method is employed in this endeavor. The difference between two probability distributions is quantified using a statistic called cross-entropy loss.

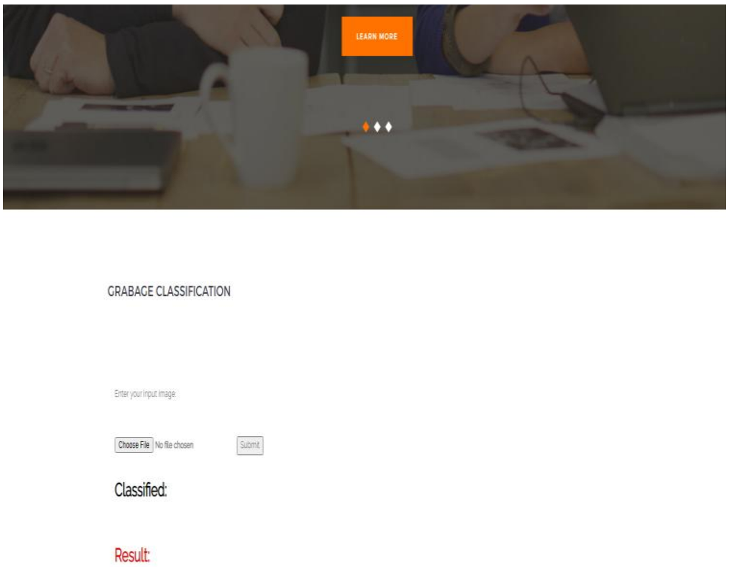
eISSN 1303-5150

4. RESULT

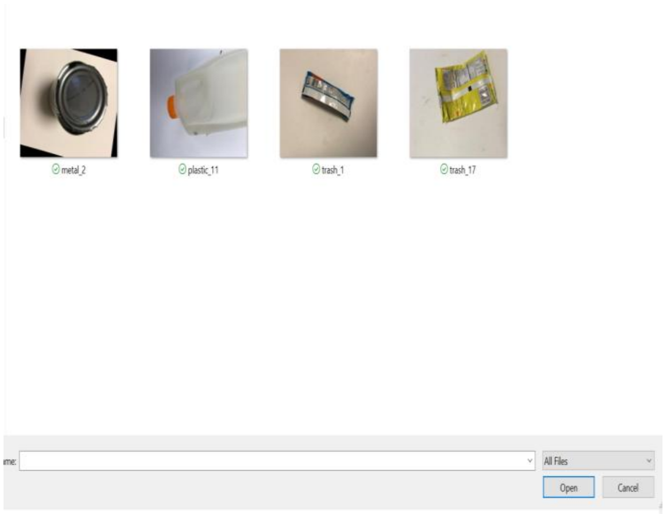
HOME PAGE



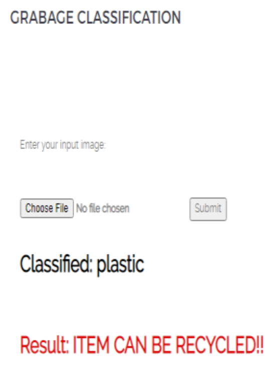
GRABAGE CLASSIFICATION



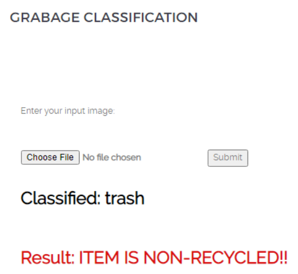
IMAGIE UPLOAD



PLASTIC RECYCLED

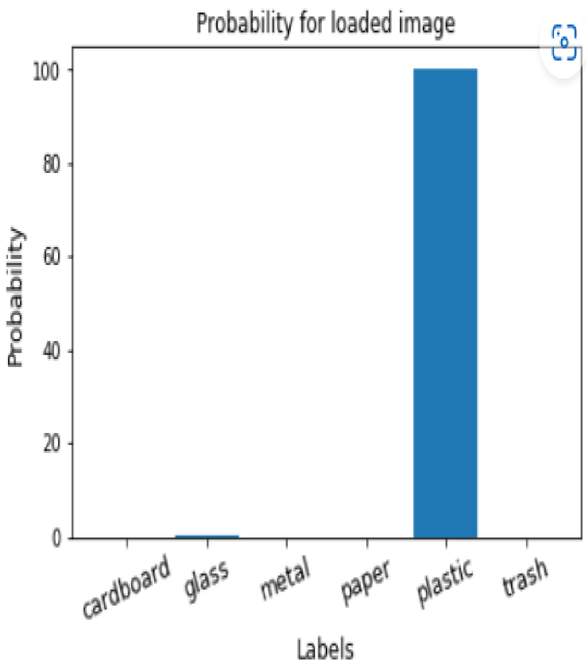


TRASH RECYCLED

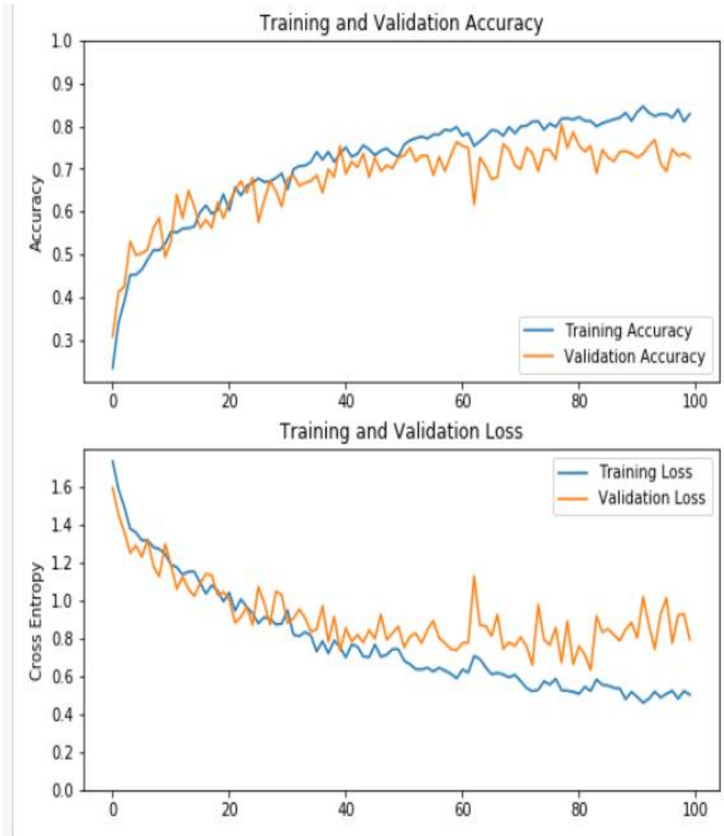


RESULT ANALYSIS

Building CNN & Saving keras model



Accuracy Graph



eISSN 1303-5150

5. Conclusion

As an example of an application of automated machine learning to industrial informatics, it demonstrated the successful identification of a recycling container being emptied based on readings from a sensor attached to the container's lid. The article suggested an iterative data-driven approach to maximize performance, which involved first evaluating the state of the art solution to the problem, then optimizing it with the collected dataset, then applying machine learning algorithms to the problem, and finally using feature engineering to determine if more features would yield better results. This research has a few caveats. To begin with, it did not attempt to quantitatively assess how much imprecise detection of emptying influences estimates of remaining volume. Second, the solutions that have been looked at depend on the fact that data on filling levels and vibration strengths is readily available. As a third issue, the computational complexity of the solutions under study was not considered. Several approaches, including the already-in-use manually constructed model, an improved version of that model, standard machine learning techniques, and those algorithms with their functionality expanded, were taken into account throughout the inquiry. Existing manually constructed models performed quite well (868%) but poorly (49% recall) on the acquired dataset. Nonetheless, by merely improving the model's parameters using the grid search on the training dataset, recall for the manually constructed model was increased to 90.5%. In particular, using the expanded features in tandem with the ensemble classifier (Random Forest) helped boost performance to 99.1% accuracy and 98.2% recall. Using the Recursive Feature Elimination algorithm, we were able to generate a set of supplementary features that included not only the current fill level but also the levels at which they would be empty in the immediate future (three hours), three days from now (twelve days from now), and twelve days from now (immediately). We also conducted an experiment to see how better emptying detection might affect the emptying time prediction. Results showed that the highest performing solution detections enhanced the current manually constructed model's emptying time forecast accuracy by 14.2 percent. After analyzing the results, we conclude that the best performing solution may be practically deployed in the production system if the condition on the availability of the measurements before and after the point of interest by twelve hours is loosened.

REFERENCE

[1]. ***[1] M. Feurer, A. Klein, K. Eggensperger, J. Springenberg, M. Blum, and F. Hutter, "Efficient and Robust Automated Machine Learning," in Advances in Neural Information Processing Systems 28, 2015, pp. 2962–2970.***

[2]. ***[2] C. Thornton, F. Hutter, H. H. Hoos, and K. Leyton-Brown, "AutoWEKA: Combined Selection and Hyperparameter Optimization of Classification Algorithms," in Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2013, pp. 847–855.***

[3]. ***[3] European Commission, "Waste," http://ec.europa.eu/environment/waste/, [Online; accessed 23-May-2018].***

[4]. ***[4] T. Anagnostopoulos, A. Zaslavsky, K. Kolomvatsos, A. Medvedev, P. Amirian, J. Morley, and S. Hadjieftymiades, "Challenges and Opportunities of Waste Management in IoT-Enabled Smart Cities: A Survey," IEEE Transactions on Sustainable Computing, vol. 2, no. 3, pp. 275– 289, 2017.***

[5]. ***[5] "Bigbelly - Smart City Solutions," http://bigbelly.com/, [Online; accessed 27-May-2018]. [Online]. Available: http://bigbelly.com/***

[6]. ***[6] "Ecube Labs - Smart waste management solution," https://www.ecubelabs.com/, [Online; accessed 27-May-2018]. [Online]. Available: https://www.ecubelabs.com/***

[7]. ***[7] "Enevo - Waste and Recycling Services Right-Sized for You," https://enevo.com/, [Online; accessed 27-May-2018]. [Online]. Available: https://enevo.com/***

[8]. ***[8] "Sensoneo - Smart Waste Management solution," [Online; accessed 27-May-2018]. [Online]. Available: https://sensoneo.com***

[9]. ***[9] "Onlab - Onsense," http://www.onlab.com.tr/en/onsense eng/, [Online; accessed 27-May-2018]. [Online]. Available: http://www.onlab.com.tr/en/onsense eng/***

[10]. ***[10] "Smart Waste — Citibrain: Smart Integrated Solutions for Smart Cities," http://www.citibrain.com/en/solutions/smartwaste/, [Online; accessed 27-May-2018]. [Online]. Available: http://www.citibrain.com/en/solutions/smart-waste/***

[11]. ***[11] "SmartBinIoT Level Sensors — Intelligent waste monitoring," https://www.smartbin.com/solutions/iot-level-sensors/, [Online; accessed 27-May-2018]. [Online]. Available: https://www.smartbin.com/solutions/iot-level-sensors/***

[12]. ***[12] B. Zhang, C. H. Liu, J. Tang, Z. Xu, J. Ma, and W. Wang, "LearningBased Energy-Efficient Data Collection by Unmanned Vehicles in Smart Cities," IEEE Transactions on Industrial Informatics, vol. 14, no. 4, pp. 1666–1676, 2018.***

[13]. ***[13] B. Tang, Z. Chen, G. Hefferman, S. Pei, T. Wei, H. He, and Q. Yang, "Incorporating Intelligence in Fog Computing***

eISSN 1303-5150

for Big Data Analysis in Smart Cities," IEEE Transactions on Industrial Informatics, vol. 13, no. 5, pp. 2140–2150, 2017.

[14]. *[14] V. Catania and D. Ventura, "An Approch for Monitoring and Smart Planning of Urban Solid Waste Management Using smartM3 Platform," in Proceedings of the 15th Conference of Open Innovations Association FRUCT, ser. FRUCT'15. Helsinki, Finland, Finland: FRUCT Oy, 2014, pp. 4:24–4:31. [Online]. Available: https://doi.org/10.1109/FRUCT.2014.6872422*

[15]. *[15] S. Sharmin and S. T. Al-Amin, "A cloud-based dynamic waste management system for smart cities," in Proceedings of the 7th Annual Symposium on Computing for Development, ser. ACM DEV '16. New York, NY, USA: ACM, 2016, pp. 20:1–20:4. [Online]. Available: http://doi.acm.org/10.1145/3001913.3006629*

[16]. *[16] J. W. Lu, N. B. Chang, L. Liao, and M. Y. Liao, "Smart and green urban solid waste collection systems: Advances, challenges, and perspectives," IEEE Systems Journal, vol. 11, no. 4, pp. 2804–2817, Dec 2017.*

[17]. *[17] T. S. Vasagade, S. S. Tamboli, and A. D. Shinde, "Dynamic solid waste collection and management system based on sensors, elevator and GSM," in 2017 International Conference on Inventive Communication and Computational Technologies (ICICCT), March 2017, pp. 263–267.*

[18]. *[18] M. H. A. Wahab, A. A. Kadir, M. R. Tomari, and M. H. Jabbar, "Smart Recycle Bin: A Conceptual Approach of Smart Waste Management with Integrated Web Based System," in 2014 International Conference on IT Convergence and Security (ICITCS), Oct 2014, pp. 1–4.*

[19]. *[19] B. Chowdhury and M. U. Chowdhury, "RFID-based real-time Smart Waste Management system," in 2007 Australasian Telecommunication Networks and Applications Conference, Dec 2007, pp. 175–180.*

[20]. *[20] J. Lindstrom, A.Hermanson, M. Hellis, and P. Ky ¨ osti, "Optimizing ¨ recycling management using industrial internet supporting circular economy: A case study of an emerging IPS2 ," Procedia CIRP, vol. 64, pp. 55 – 60, 2017, 9th CIRP IPSS Conference: Circular PerspectivesonPSS.[Online].Available:http://www.sciencedirect.com/science/article/pii/S2212827117302184*