ANALYTIC OPTIMIZATION FRAMEWORK FOR RESILIENT MANUFACTURING PRODUCTION AND SUPPLY PLANNING IN INDUSTRY 4.0 CONTEXT-BUFFER STOCK ALLOCATION – CASE STUDY

Optymalizacja planowania produkcji oraz zakupów w środowisku analitycznym dla elastycznej i odpornej organizacji produkcyjnej w kontekście Industry 4.0 – studium alokacji buforów

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Abstract: Advanced components assembly planning and related manufacturing production planning and scheduling (PPS) and supply planningare key elements responsible for deliveries and cost aspects as a resources workload and inventory driver. Industry 4.0 systems broaden science for improving system performance and decision making.Industry site environment because of material flow network, interrelated multi-variable, multilevel production becomes very complex what is challenged by a strong focus on operational excellence. Demand uncertainty requires additional attention and integration with Supply Chain. This paper presents an extended framework for analytics solutions in assembly, production and supply planning for manufacturing company. Risk related to violable customers demand is mitigated by buffer management. Buffer levels relay on a prediction from simulation model using computational methods based on machine learning algorithm using Neutral Networks to guarantee on-time deliveries and rational costs. Actual challenges and requirements for new use cases in data-driven intelligence are presented. The proposed models and the actual state will be comparably discussed with results analyses.

Keywords: Manufacturing Data analytics, Resilient manufacturing, Production planning, Buffer management

Streszczenie: Planowanie montażu zespołów i wynikające z niego planowanie i harmonogramowanie produkcji (PPS) oraz planowanie zakupu surowców są kluczowymi elementami odpowiedzialnymi za dostawy na czas oraz aspekt kosztowy poprzez odpowiednie obciążenie zasobów oraz nośnik zapasów. Systemy klasy Industry 4.0 poszerzają wiedzę i możliwości dla podniesienia wydajności systemu oraz usprawniają podejmowanie decyzji. Środowisko produkcyjne z uwagi na sieć strumieni wartości, mnogość zmiennych, wielopoziomowe struktury materiałowe staje się bardzo złożone co jest dodatkowo wzmacniane przez nacisk na doskonałość operacyjną. Niepewność zapotrzebowań wymaga dodatkowej atencji oraz integracji z łańcuchem dostaw. W pracy zaprezentowano rozbudowane środowisko dla rozwiązań analitycznych wspierających narzędzia planowania montażu, produkcji oraz zakupów. Ryzyko związane z zmiennymi planami klienta oraz zmiennością dostawców jest ograniczane poprzez zarzadzanie buforami. Poziom bufora zależy od predykcji na bazie modelu symulacyjnego opartego na mechanizmach uczenia maszynowego z wykorzystaniem sieci neuronowych w celu zagwarantowania dostaw na czas oraz w oczekiwanym koszcie. Aktualne wyzwania i oczekiwania w obszarze inteligencji opartej na danych zostały zaprezentowane. Rezultaty zaproponowanego modelu zostały szczegółowo porównane ze stanem obecnym.

Słowa kluczowe: Analityka produkcji, Elastyczna i odporna produkcja, Planowanie produkcji, Zarządzanie buforami

Introduction

Assembly planning in industry environments is influenced by volatile markets, the high complexity of products and dynamic production conditions. Companies offer discrete products while maintaining low costs and reducing lead time to remain competitive. [7] Carvajal Soto, J. A., Tavakolizadeh, F. and Gyulai, D. Actual situation show that ability to become more vulnerable to disruptions is a key to run manufacturing organizations successfully. In this uncertain environment quick what-if answers, optimization and data modelling are a powerful tools for learning insights and improving decision making. [14] Daniyan, Muvunzi, Khumbulani. Various sources of data generated in a massive amount, include a huge potential and causes the need for further analysis and predictions. This involves the construction and training of a machine learning model that without experts knowledge is very challenging. Multiple data are coming from Industry 4.0 Systems into Company's databases. Those acquired data are the next characteristics that can better describe the nature and needs of the organization and finally help to find the best data- driven intelligence for decision making. These data can be used to make strategic planning, process control and monitoring. It will also help in long-term problem solving. Multiple optimized algorithms are included in Industry 4.0 systems. [20] Nagorny, Lima, Monteiro. By using data from multiple sources a new optimized possibilities are provided and more accurate recommendations can be set for better decision

making. Information on the process outputs at each stage can be useful in improving performance and helping better understand current state. Machine Learning (ML) powered systems are a very promising way of achieving process monitoring which can lead to significant improvement in whole production and supply planning. Optimized safety stock levels have increasing research attention in last decade. Cost of material shortage can be significant when considering the cost of resources waiting (employees performance, lack of machines utilization), material flow dropdowns, customers delivery delays. Dolgui, A. and Prodhon [9] show that different types of buffers may be employed to improve performance but they should only be used when the contribution of a buffer is greater than the cost of it. Management of buffers is an important part of manufacturing planning and controlling (MPC) in order to stay competitive. Dolgui, A. and Prodhon [9] defined a framework for MPC that reflects the significance of buffers. To support the balancing of supply with demand they identified four management perspectives. Buffer management is defined based on the intersection of four management perspectives related to the transformation flow: the resources employed in the flow, the risk involved in the flow, the decision making. In volatilised and uncertified environment buffer strategy also has to have the ability to change quickly because it may lead to redundant inventory levels. The aim of that research is to present the use of ML to enhance the performance of a value stream from assembly to production line and supply as a case study by providing a recommendation for buffer location and safety stock levels. The proposed framework can be used for further research and designing algorithms for data mining.

This paper is constructed in six sections. The second section focuses on the state of research. The third section introduces the used analysis framework. The next fourth section describes methodology and modelling. The fifth section examines and analyses the results of the research. The last sixth section presents the conclusion and further research perspectives.

State of research

We are surrounded by digital environments continuously generating more data and with connections to devices and software. Such an evolution happens also in the manufacturing domain. Future Smart Manufacturing infrastructures are faced with the digitalisation and virtualisation of objects enhanced with sensors, processors, memory and communication devices. That is providing the ability to communicate coactively and to exchange information independently through a reactive, predictive behaviour [6]. Massmann et all [19] described a framework for data analytics in Data -Driven Planning. That's addressing the major challenges in the context of analytics activities and the resulting requirements. Along with the four layers of analytics projects, the framework proposes procedures and methods that support the planning and implementation of a successful data analysis in product planning. Research has proven that it is advantageous to employ algorithms with self-learning abilities as their predictive abilities often increase over time with an increase in the size of the data [9-11]. Besides, it can reveal new failure modes and give insights into the asset reliability model [2-4]. Machine learning algorithms have become more and more popular over the last decade for production applications, which can lead to better-suited recommendations for decision-making managers[12]Because of high changeability in organizations surrounding companies are looking for methods for risk mitigations and being resilient. Supply chain resilience was discussed in literature widely. Hosseini et al [11] reviewed quantitative methods , technologies and key drivers of supply chain resilience. Hosseini, S. and Ivanov, D., [10] proposed resilience measure as a function of supplier vulnerability and recoverability using a Bayesian network and considering disruption propagation .That allows to uncover higher-risk suppliers to develop recommendations to control the ripple effect. In literature. Many different methods and approaches in fixing buffers under different situations can be found in literature. Aleotti and Qassim [2] concluded that holding inventory in the intermediate levels which only reduce the frequency of stockout is not economical. Li and Li [17] showed a dynamic model of the safety stock. Only the variability of demand is considered in this model. Authors also presented another method for a multilevel MRP system. The relation between safety stock and different system measures like service level, schedule variability, and total cost in different methods has been provided. Bahareh and Bhuiyan [6] present a general safety stock optimization model with the objective of logistics cost minimization by considering both internal and external variabilities. Authors also consider part availability (First Fill Rate FFR). Demand and Supply variability are addressed in [19]. Authors provide research about the required amount of safety stock or the length of a safety lead time influenced by the level of uncertainty experienced in a production unit. Karaesmen et al [16] present that there is an impact of increased un certainty in demand and supply variability to decrease delivery performance. Recent reviews on managing uncertainties in MRP environments show that, to date, studies have been largely restricted to a single source of uncertainty, related to either supply or demand. Hedvall [18]identified and constitute the foundation for buffer management in: Balance management (Demand and Supply), Resource management (Materials and Capacity), Risk management (Regular and Safety), Hierarchical management(Structural, Aggregate, Detailed and Execution). That hierarchical split is then shown in additional 4 dimensions- Material Management (MM) and Capacity Management(CM) with regular and safety approach – That gives sixteen components of buffer management. No use case or practical aspect was shown. Amirjabbari and Bhuiyana [5] presented a safety stock optimization model with the objective function of total logistic costs

minimization with an optimal level and location of safety stock across the supply chain.

The available research publications use mostly standard data like ERP and do not cover complex buffer model addressing both supply and demand variability with manufacturing aspects in internal process and additional data availability. Dynamic buffer modelling with Machine Learning algorithm sand a wider view based on new data view from Industry 4.0 systems for securing production planning is presented in this paper. This industrial problem represents another interesting and challenging research opportunity especially due to the resilience aspect igh variability, responsiveness and flexibility expectancy with continuous cost perspective.

Framework

Analytics solutions in production and supply planning for a manufacturing company need strong data-driven intelligence based on Industry 4.0 systems. The analytics framework schema is shown in Figure 1.

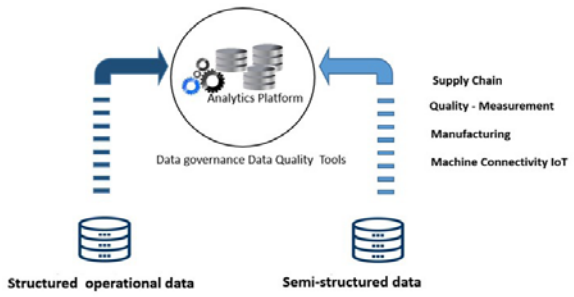

Fig. 1. Analytics framework

Analytics platform gathers, combine, cleanse and enhance data from two types. Except for structured operational data e.g. ERP system data and other supporting ones which extend business data framework needs to address also those less-structured ones. Those data are coming from Industry 4.0 systems like Machine Connectivity, Manufacturing IoT, Measurements, MOS. IoT data like machineries signals providing detailed information about the way that manufacturing organization works may also give valuable information in terms of production planning and raw material availability.

The below framework can be consumed by various users and tools shown in a Fig. 2.

Analytics models as a computed portion of data with detailed information prepared with a business goal are consumed by Self-Service solutions. They ensure data re-use for personal /ad-hoc data exploration, outside of formal projects. Data investigations in self-serve mode serve for generating initiatives and projects. Analytical tools help to improve process and information flow. They are reusing data collected and stored in Analytics framework. Advances Analytic sis a decision support as the ultimate goal of analytics solutions – data driven decision making based on recommendations found in data. The process of manufacturing data modelling is shown in Fig. 3.

Data modelling for defined questions based on Machine Learning algorithms needs strong and scalable data acquisition and storage steps. Then data pre-processing for preparing and cleaning is set. Process definition and key variable identification is the next element. Then data exploration and data training is performed. Model development is the last step.

Fig. 2. Data consumption

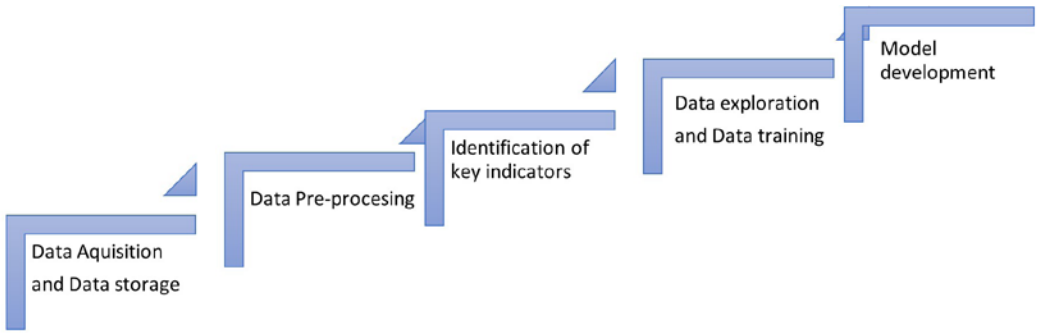

Fig. 3. Data modelling process-Machine Learning

Methodology and model

Effective buffer management (right places, levels and types) is the key element for manufacturing risk management for production and supply environment and a variability on both sides. All parts availability on time allows to finish assembly on time for customer demand and provide resources workload according to plan. Lack of components at any point of production leads to material flow distortions. Risk management in that area is evaluated thought buffer management. That is guaranteed through safety stock (SS) or safety time (ST) or mixing policy. Buffer level, type and location should also consider the optimized level of costs. Costs of resource waiting, the material flow stops and customer waiting should be compared to the cost of additional inventory storage. The research was carried out on data coming from company A – for the purpose of confidentiality. A is a manufacturing company. A has a complex multi-level bills of material, high demand variability and long lead times. Numbers of suppliers, procurements, manufacturing, final assembly, and customers (internal and external) are different nodes of the A's supply chain. That advanced system focuses significant attention on setting and positioning buffers. Data used in research covers two years history of inventory levels, overdue, shortage history gathered in weekly snapshots. Based on CRM, ERP demand variability was calculated. Historical parts availability is calculated based on ERP and Manufacturing systems. Data are additionally cleaned from used buffer methods to have full visibility in the real environment. Additionally a big number of another parameter and variables gathered in Industry 4.0 systems were included in modelling. The results are limited to the selected Final Assembly family composed of 29 part numbers that represents one of A's production lines. Sample Bill of Material for particular Finish Good (FG) assembly is shown in Fig. 4. The green colour indicated raw materials (RM), blue are manufactured (MFG)

The objective is to minimise the overdue of raw material and subassembly for production and thus avoiding production material flow breaks and assembly picking issues for on-time delivers to the customer while not exceeding the level of cost. Parameters and variables are listed in Tab. 1. Those variables affect the final state of material availability and create the integrated model. Used variables impact on a buffer management model.

Table 1. Parameters and variables

M	Number of Final Assembly i
N	Number of Sub-Assembly j
O	Number of Component k
p	Date
a_k	Number of Supplier for Component k
b_{kp}	Planned delivery time of Component k
c_{kp}	Inventory-stock of Component k in historical snapshot p
d_{kp}	Overdue-Missed parts of Component k in historical snapshot p
w_{knp}	Balance of Component k in weeks n in historical snapshot p
e_{kp}	Overdue deepness – Missed parts of Component k in weeks for historical snapshot p
f_{kp}	if item d_k<0 , 0 otherwisein historical snapshot p
w_{kp}	Demand of item k [Weekly – average for next 8 weeks] for historical snapshot p
g_k	Demand variability for Component k
h_k	Supply variability for Component k
l_{kp}	Number of Production Orders that cannot start because of lack of k for historical snapshot
m_k	Segment volume for Component k
n_k	Bill of Material level for Component k
r_k	Cost Segment for Component k
s_k	Volume Segment for Component k
t_{kp}	Component k availability measurement (FFR) in historical dates
T_{mp}	Final Assembly m availability measurement (FFR) in historical dates
u_{kp}	Type of Component k in historical dates
z_{kp}	First Pass Yield (FPY) Quality grade of k in historical dates
C_k	Cost of shortage for Component k in historical snapshot p – resource waiting
O_k	Cost of overstock for Component k in historical snapshot p – inventory

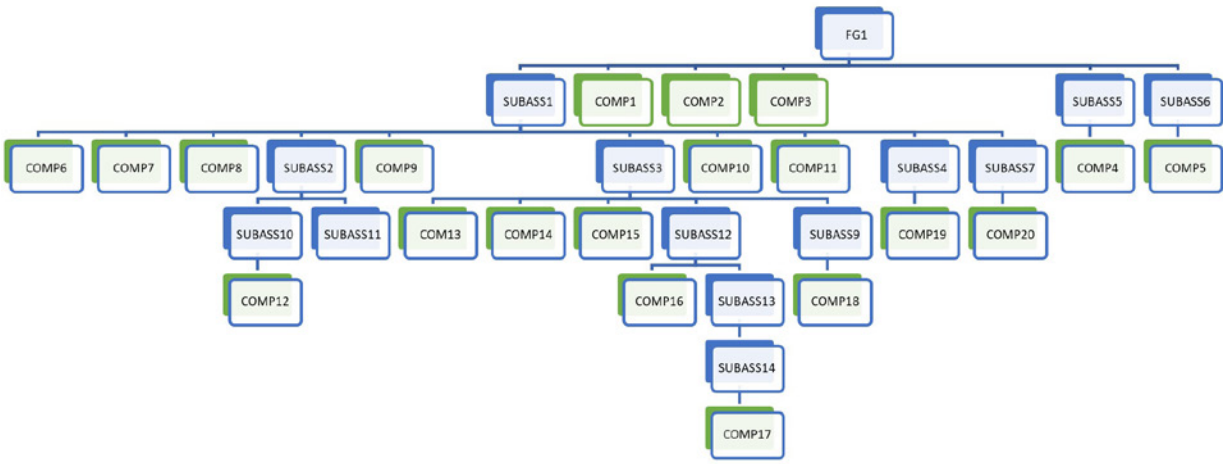

Fig. 4. Sample Bill of Material

Multilevel bill of materials for 29 Final Assembly Parts *i* with an average 35 Components *k* and an average 13 Sub-Assembly j is a complex modules model framework. Place in BOM structure n_k impact significantly material availability. Historical datashow structure forthe deepness of overdue e_{kp} and accompanying values of demand level w_{kp}, supply and demand variability g_k, h_k, quality z_{kp} in that period. Also parts parameters for that period were included like Planned delivery time (LT) b_{kp}, type u_{kp}.Those elements have multiple sources (suppliers a_k or manufacturing lines), prices r_k and volume segments m_k that determine the costs of inventory. For buffer calculations were included also costs of shortage. Data used to create that information are coming from Industry 4.0 systems. Machine waiting and manpower resources waiting costs calculated based on above data. The complex module structures cause multiple shortage issues. For example – We may have available 100% components on time and still will not be able to provide part on time because of quality or resources problems. That is why we also include FFR value for Subassembly *j* and Final assembly *i* in snapshot (*p*).

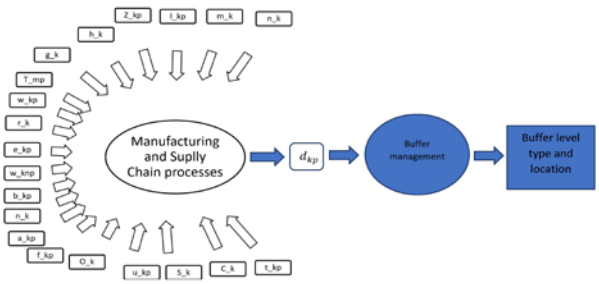

Fig. 5. Buffer management module

Output from Manufacturing and Supply Processes is reflected in material balance /Overdue d_{kp} as a material availability score in snapshot p. It is a balance of stock level and past requirements for component *k*. The result variable has a distribution shown in Fig. 5. Values d_{kp}<0 means that there is a shortage and planned orders cannot be converted into Work In Process.

Data distribution for d_{kp} result by components is shown in Fig. 6.

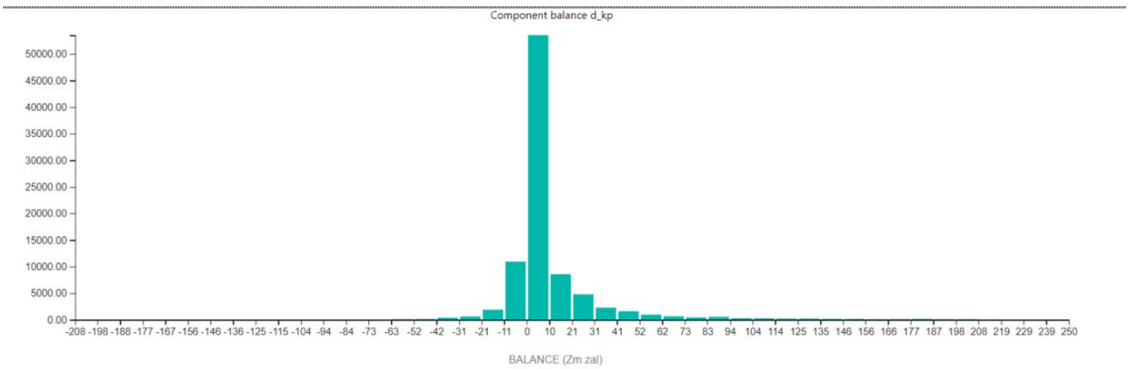

Fig. 6. Material balance d_{kp} data distribution

For better visibility one particular final assembly components distribution is shown in Fig. 7.

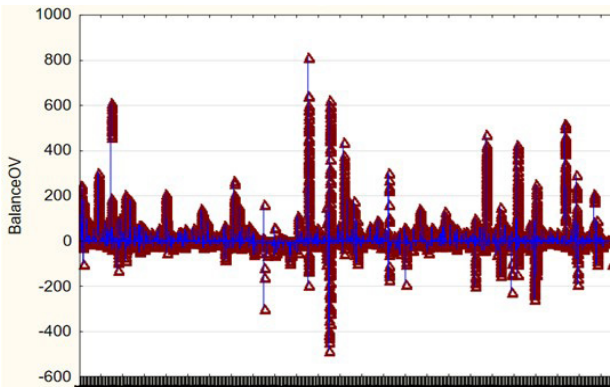

Fig. 7. Data distribution for d_{kp}

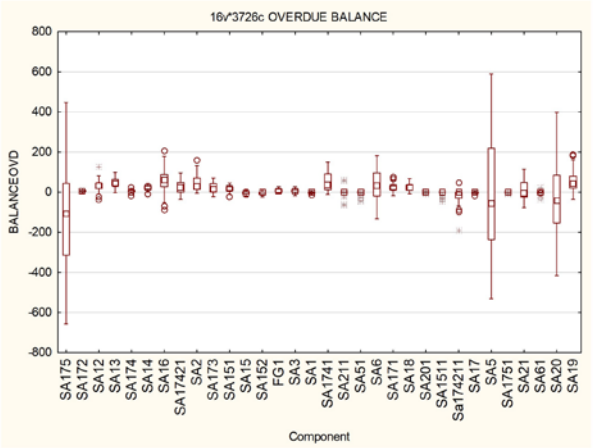

Fig. 8. Overdue boxplot

The first conclusion about buffer allocations can be made for those components that have a median below 0. Recommended buffer level needs additional data modelling. As a result of the production and supply environment and a variability on both sides it is the key element for manufacturing risk management to provide buffer management in the right places, levels and types. The Machine learning model is proposed to create a dynamic self-learning algorithm to predict future material balance for shortage cases based on mentioned set of parameters and variables. That model could predict future level of balance on components and then provide the answer in buffer allocation to mitigate that risk and guaranty material availability.

Results present analyses

Artificial Neutron Network MLP

An artificial neural network (ANN) was developed to predict the material balance d_{kp} for components in time. ANN structure consists of input, hidden, and output layers for the estimation of material availability. The hidden layers consist of different nodes for the estimation of the output. For the development of ANN, 21 parameters were considered as inputs including: demand and supply variability in last period, Component FG, average demand for next 8 weeks, supplier, Planned LT, Batch size, FPY in the last period, Bom level and Bom structure. Linear functions were used as the transfer function in the hidden layer. The optimum ANN topology was obtained by trial and error, and the ANN structure is shown in Fig. 9. As seen, the ANN takes multiple parameters as the inputs, and estimates the material balance d_{kp} as the output. *Statistica 13.3* software was used for performing the ANN analysis.

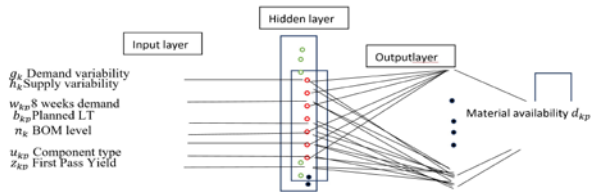

Fig. 9. ANN structure

Data were divided into learning (70%), training (15%) and validation (15%).ANN Model results are shown in Tab. 2 and Fig.10

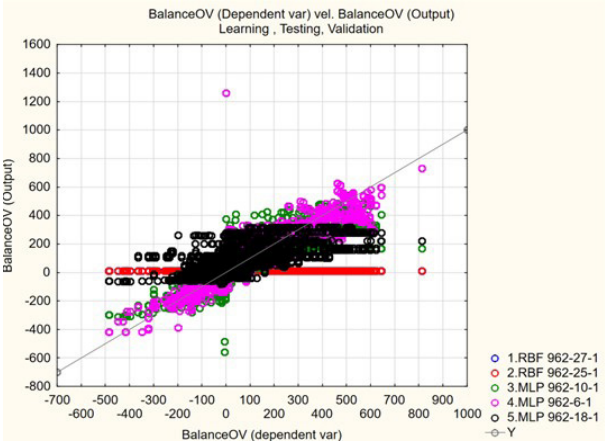

Fig. 10. NN Learning results graph comparison

The best results are captured in network 4 with Exponential activation (hidden). It is a Multilayer Perceptron type of network. The used algorithm is BFGS 6754.Realvaluescomparable to those produced by winning network 4 are shown in Fig. 11.

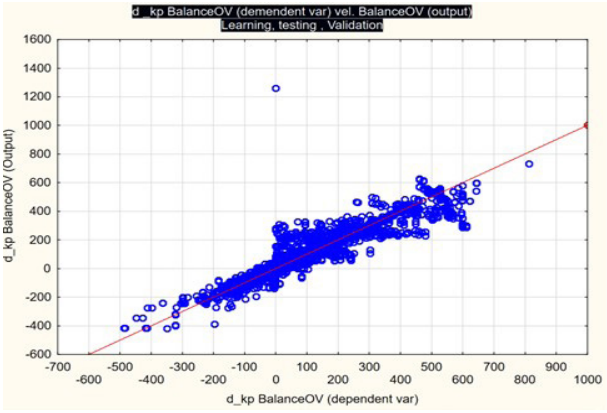

Fig. 11. Winning network-data comparison

The results show that MLP can provide very good rules in future projections based on data. The difference between captured real data and those produced by Neutral Networksis 6.5% (93.5% accurate).The detailed information shows a great opportunity to use trained Network to provide projections for future levels of components balance d_{kp}. The structure of differences between captured and projected data for the data set is presented in Fig.12.

Table 2. ANN Learning results comparison

Id sieci	Nazwa sieci	Jakość (uczenie)	Jakość (testowanie)	Jakość (walidacja)	Błąd (uczenie)	Błąd (testowanie)	Błąd (walidacja)	Algorytm uczenia	Funkcja błędu	Aktywacja (ukryte)
1	RBF 962-27-1	0.000000	0.000000	0.000000	854.1504	911.3160	983.0272	RBFT	SOS	Gaussa
2	RBF 962-25-1	-0.000000	0.000000	0.000000	854.1504	911.3160	983.0272	RBFT	SOS	Gaussa
3	MLP 962-10-1	0.899685	0.885158	0.892778	163.2220	197.4026	199.9295	BFGS 95	SOS	Logistyczna
4	MLP 962-6-1	0.952398	0.944205	0.916645	79.3877	98.8196	158.5997	BFGS 6754	SOS	Wykładnicza
5	MLP 962-18-1	0.764975	0.780491	0.762031	354.3135	356.7371	412.2092	BFGS 161	SOS	Liniowa

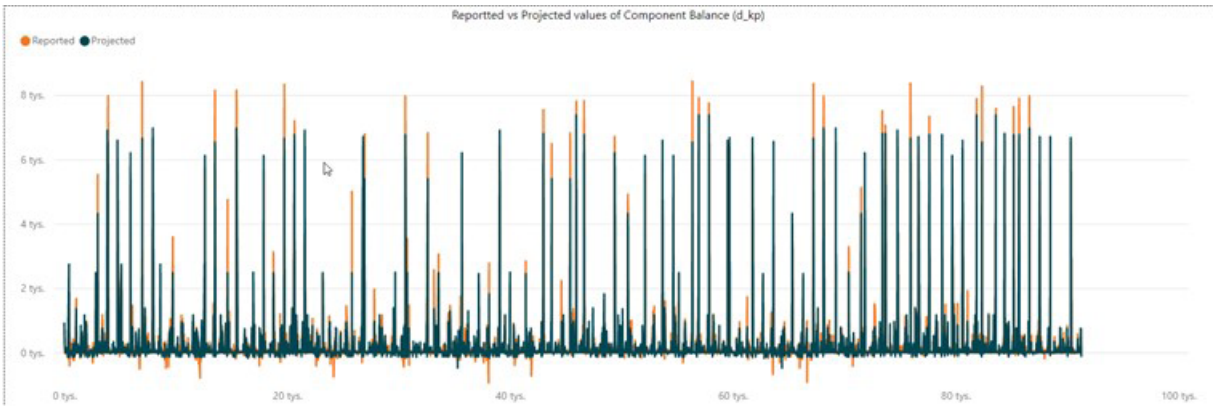

Fig. 12. Reported and Projected values

For better visibility data for individual component 403 is shown in Figure 13

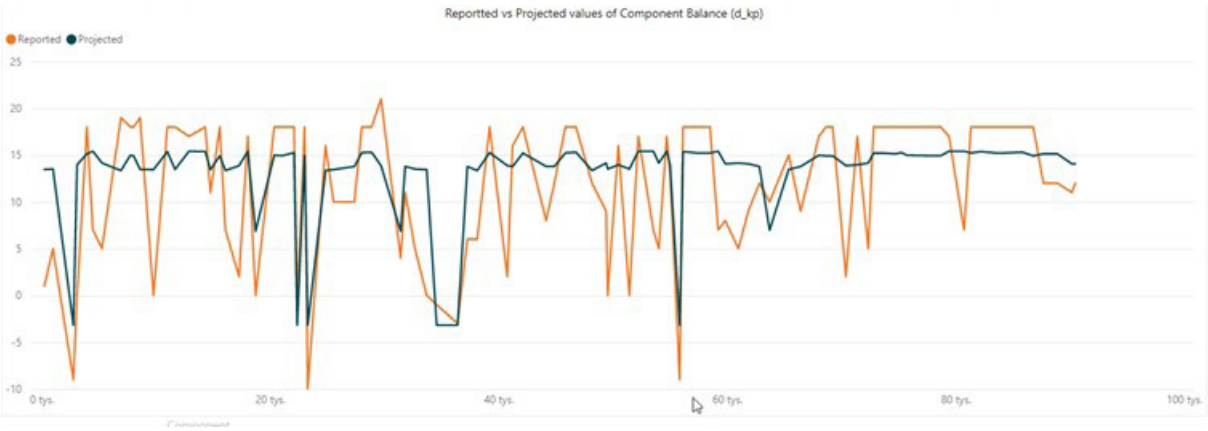

Fig. 13. Component 403 reported and projected values

That means that better than any other statistical method or approach Neutron Network can predict how violable market will perform in way of the balance of material. Having that information and combining it with other variables is a key element for risk mitigation by recommending levels and locations of buffers.

Neutron Network data consumption to buffer levels recommendation

Projected values from Neutron Network and other defined variables are included to build an analytics model to recommend buffer levels, location and types. Key elements considered in modelling:

- *Projected values from Neutron Network*

When projected values are below 0 (shortage) they need to be secured by implementing a buffer strategy. The recommended levels will exceed it to provide week up to three weeks of buffer depending on other variables

- *Median value from Historical Data*

In a quickly changing environment it's critical to react quickly. If the median value for Component balance is below 0 then a physical inventory buffer will be proposed in the Safety Stock type of buffer. If shortage situation is frequent and median is around 0 and overdue is more connected to supply variability then safety time (ST) will be proposed. When the shortage situation is rare and median is high then a more elastic form of the buffer will be recommended like Dynamic Safety Stock (coverage profile in ERP).

- *Cost aspect*

As mentioned in the literature review it is economical and organizational profitable to keep buffers. The components from high cost segment will have a lower buffer then those medium or low. The situation where the costs of inventory offset costs of shortage and low delivery performance also were included.

- *Component parameters*

Lead times, batch sizes, type of component, supplier type also impact buffer management policy.

Analytics Model is prepared to work dynamically with ANN. Model is produced on the platform described in Figure1. Kampen et all [23] present research for using Safety stock and Safety Time depending form the source of variability. Partially it finds confirmation in this paper. Static forms of buffer were proposed on locations where we see the projection of shortage and it happened often in history based on median. Safety stock (SS) was proposed there where ANN forecasts shortage and historical median set shortage frequent. Safety time (ST) was proposed in low levels on projected balance with historical shortage situations. The rest of the population was covered by Dynamic Safety stock. They are defined by Coverage profile which works on average daily requirements. It is calculated depending on the requirements within a specified period (e.g. 6 months) and the range of coverage (e.g. 3 weeks). That elastic form of buffer matches demand. Additionally working in a range of coverage it works from the minimum up to the maximum level being very elastic and guarantying on time material availability.

The results of experiments show that the received target inventory value level is lower than firstly predicted in NN. That show that thanks to Machine Learning and Mathematical programming and modelling it is possible to guaranty material availability by mitigating the risk of shortage with correct buffer levels, location and type without additional investment. Reducing big numbers of inventory in one place and setting buffers is a key to the proposed dynamic approach. The projected level of balance (planned inventory) was firstly 482.36 KPLN. The new Buffer structure will recure a maximum of 349.02 KPLN. Difference values split for Final Assemblies is provided in Fig. 14.

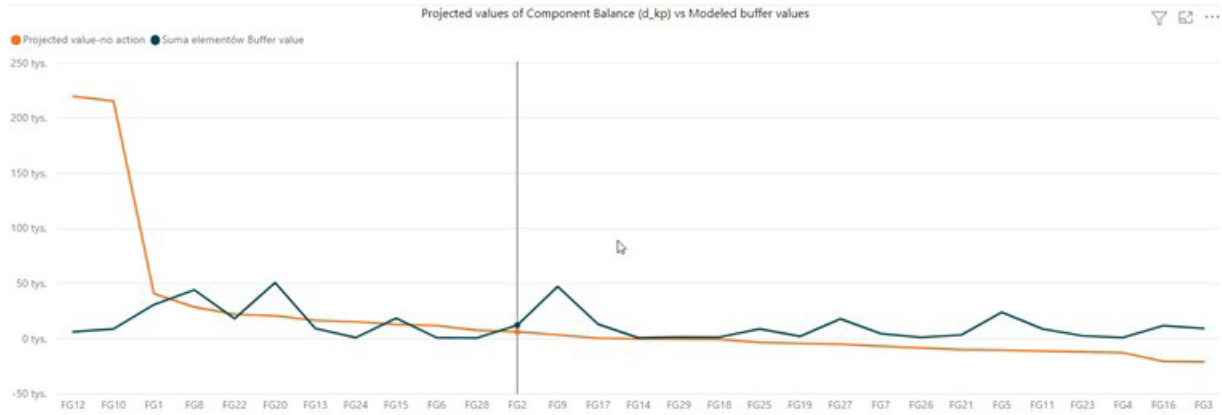

Fig. 14. Comparison of projected inventory and new buffer value

Used buffer types split is shown in Fig. 15.

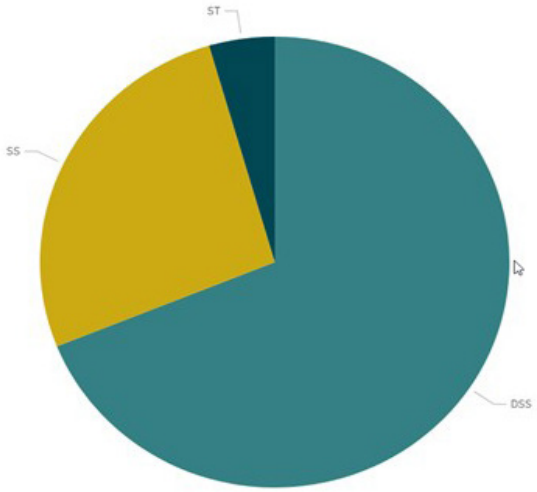

Fig. 15. Buffer types split

The above analyses show that Machine Learning combined with analytical modelling can give organizations new possibilities to optimize buffer management process, increase performance and profit.

Conclusions and future research opportunities

In this research, a dynamic and data driven buffer management optimalization model is provided with the objective function on buffer location, levels and types. Modelling is based on predictions from Neutron Network for future material balance (inventory or shortage) combined with other variables defined. Practical real-world problem with different value streams was used during research. The proposed methodology which joins Machine Learning algorithms and risk mitigation analytical modelling make the system less vulnerable to demand and supply changes.

In this paper, we presented an approach that optimizes the buffers placement in a manufacturing company production line. We find in our experiments that thanks to a data-driven approach combining Machine Learning and other algorithms we may guaranty on time delivery without additional investments. Target inventory levels should be rearranged due to demand change. Buffer realignment based on dynamic modelling should be adjusted when data and trends are changing as fast as possible. By enhancing the visibility and control of key elements in value stream in the chain, the optimization model can be

applied for each specific part. By increasing the accessibility of the data, and new data views it is possible to bring more information from the data and using them for optimizing products and processes in the company.

Several promising directions for further research remain like factors of waiting time for receiving the late parts, safety stock for the finished assembled product, and build ahead in making the decision for the buffer placement. An another direction for further research is extending the applied methodology for other processes in Production Planning and Control.

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