IMPROVING SUPPLY CHAIN RESILIENCE THROUGH METHODS OF FAST ADAPTATION TO SUDDEN DEMAND SHIFTS IN THE TIME OF CRISIS

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Abstract

Supply chain resilience is a topic long discussed, however, spread of the newly emerged COVID-19 virus pandemic in 2020 and subsequent application of measures to deal with it had strong impact on supply chains. One of the challenges of 2020, which companies had to face, was a sudden change in demand. While commonly known forecasting methods are able to estimate demand that behaves according to the historical experience, need for different approach to sudden shifts in demand both up and down, arose. Research into comparison of such methods was carried out and they were tested on data from the outbreak of COVID-19 virus pandemic crisis in the Czech Republic, when applied measures and concerns of people caused a significant change that had impact on the demand for various goods.

Key words: supply chain, supply chain resilience, demand forecasting, Covid-19, mean absolute percentage error (MAPE)

1. INTRODUCTION

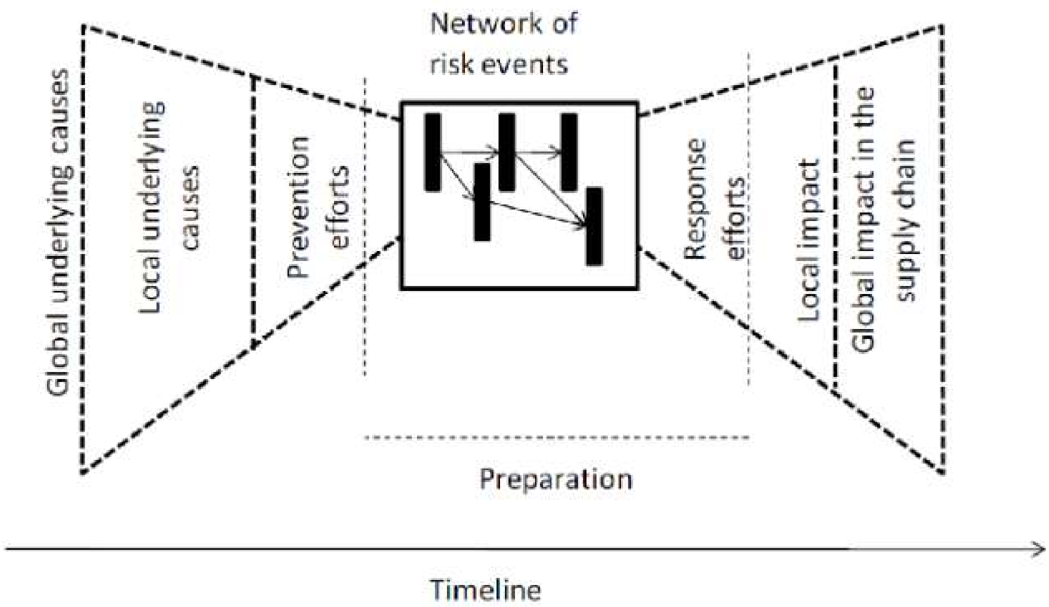
A famous quote of Danish origin (mostly incorrectly attributed to Niels Bohr) says that: *"It is difficult to make predictions, especially about the future…"*. This opinion is widely accepted, although many scientists work hard to make their predictions as precise as possible, not to mention many demand planners, trying to predict the "unpredictable". What worries those people most is the situation when some previously unknown variables appear. These can be sudden demand which increases or decreases respectively, or potential deviation, disruption or disaster affecting supply chains (Tang, Chung-Piaw, & Kwok Kee, 2008). War conflicts (e.g. Iraq 2003-2007), natural disasters (e.g. Taiwan earthquake in 1999, ash-cloud from Islandic volcanoes, or earthquake in Japan in 2011) can be considered such events with critical consequences to the part or the whole global supply chains (Dvorak, Sventekova, Rehak, & Cekerevac, 2017) and (Bernatik, Senovsky, Senovsky, & Rehak, 2013). One of the latest events was the outbreak of the COVID-19 virus pandemic crisis and its mitigation, especially during March and April 2020.

Although there is an ongoing expert discussion dealing with the potential consequences of COVID-19 virus pandemic on the overall social lives, business and international trade, there is not unequivocal consent, especially on the long-term impact, proper reactions and further appropriate prediction possibilities (Tulach & Foltin, 2019). The truth is, that the impact of COVID-19 virus pandemic crisis on the natural global supply chains reached all three standard broad forms of the management of risk in global supply chains - deviation, disruption and disaster to supply chains, where (Christian & Griffiths, 2016):

- Deviation occurs when one or more parameters (e.g. costs, demand, lead-time, etc.), within the supply chain system stray from their expected or mean value without any changes to the underlying supply chain structure;
- Disruption occurs when the structure of the supply chain system is radically transformed, through the non-availability of certain production, warehousing and distribution facilities or transportation options due to unexpected events caused by human or natural factors;
- Disaster is defined as a temporary irrecoverable shut-down of the supply chain network due to unforeseen catastrophic system-wide disruptions.

Due to overall consequences to global supply chains, material, information and financial flows, COVID-19 virus pandemic crisis could be categorized from a global point of view as a disaster to supply chains. From regional point of view the mixture of the disruption and disaster appeared. Similarly, post COVID-19 consequences as disruption, due to previous deep disfunction of supply chains, but also due to creating oversupplies individually stored in companies´ warehouses and individual properties can appear (Volkin, 2020). For prediction of future demand for stocks and reaction to the need of society and business (Urban & Hoskova-Mayerova, 2017), it is necessary to keep in mind preventive measures reached in advance before the crisis occurs, immediate reaction during the crisis, and reaction later during the phase of supply chains reconciliation and restoration. These supply chain security, resilience and recovery requirements were properly represented by Brian and Griffiths as a butterfly depiction of the risk in supply chain network (Christian & Griffiths, 2016), see Fig. 1.

Figure 1. Butterfly depiction of risk by a network of risk events.



Source: (Christian & Griffiths, 2016)

There are sets of preventive, immediate and reactive measures on global and local levels (Foltin, Vlkovský, Mazal, Husák, & Brunclík, 2018).

2. CURRENT APPLICABLE METHODOLOGICAL APPROACHES

Although basic forecasting methods are known for decades, e.g. (John, Satinder, & Donald, 1971), many organizations still rely on human expertise in forecasting and ordering process. This can partially be an advantage in sudden changes in demand as people dealing with demand forecasting can spot the change to deal with it with more or less success. Current trends in supply chain digitalization focus more on employing systems where forecasting methods are used with various degrees of human assistance.

2.1. Forecasting methods

Common approach to demand forecasting, based on data and quantitative methods, is time series analysis, pattern searching and causal model. Both time series analysis and causal models rely on past time series data and although neural networks and pattern searching methods are now more available, still those methods are not able to forecast any sudden change that did not occur in the history. Essentially, they try to extract the future from the past.

2.2. Ordering based on forecast

Most commercial software packages use some variations of reorder point (ROP) ordering. If *reorder point* is reached then the order is generated. However, determination of reorder point is the most difficult task. Common approach is based either on average consumption during the lead-time or forecast during the lead time. Both can be added by a safety stock as a measure against uncertainty in both lead time and forecast or average demand.

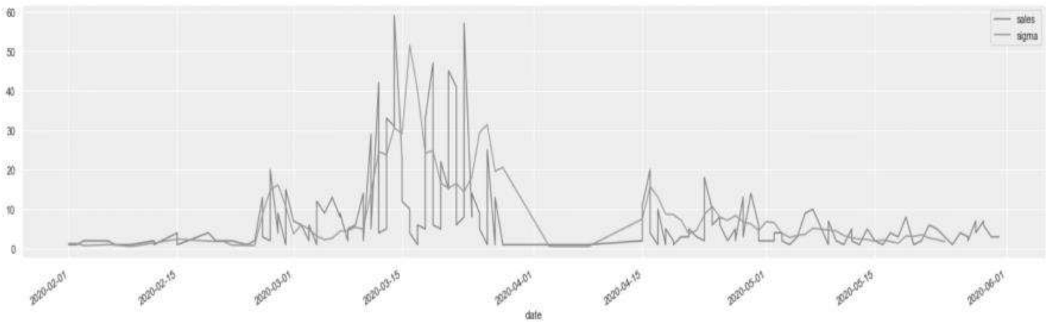
Safety stock is calculated based on the error of forecast. None of them is prepared for the situation when forecast error rapidly increases or when current demand significantly diverges from the past demand. See Fig. 2 for sales of soap and standard deviation of the forecast calculated based on past 180 days with a testing period of 2 days on which the deviation is calculated as:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{k} S_i - {F_i}^2}{N - 1}}$$

where:

- S_i … sales for a given period
- F_i … forecast for a given period
- N … number of periods

Figure 2. Sales of soap with standard deviation of forecast



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Potential to use the calculation of standard deviation for calculating reorder points is discussed in further sections.

2.3. How fast can traditional methods react

The issue with traditional time series methods is that they may not be fast enough to react to sudden change in demand (Foltin, Gontarczyk, Swiderski, & Zelkowski, 2015). Forecasting process is often done monthly or weekly and the corresponding ordering process is based on either the split or daily share of forecast. The ability to react to change is then the length of the forecasting window. So, if the forecasting is done on a monthly basis, the time window for reaction is one month. This is usually not a problem if orders are issued once a month, but in dealing with fast moving consumer goods in retail it is usual to react more often, even on daily basis. There are several approaches to deal with forecasting of daily data. One is the method of calculating daily ratios and splitting the monthly forecast accordingly. In retail, it is often a better approach as sales tend to be heavily influenced by days in the week, holidays and similar factors. If the ordering model based on sum of forecasted sales in the lead time period is used, forecast for that period must be calculated first. To do so, a finer granularity of data to be taken into account is needed. However, relying on monthly forecast in the time of disruption is not fast enough. With this approach, the process should deliver suggestions based on the wrong data. It is clear that the daily data to trigger a new process must be monitored if it indicates the sudden change in demand.

3. RESEARCH AND METHODOLOGICAL APPROACH TO THE SUPPLY CHAIN DURING COVID-19 VIRUS PANDEMIC AND POST COVID-19 VIRUS PANDEMIC SITUATION

Manufacturers, that rely on labour-intensive processes that require people work closely together, were disrupted because of social distancing requirements. Similarly, production that relied on spring harvest might have been in short supply in summer due to labour shortage (Volkin, 2020). Similarly, transportation routes were at risk due to potential COVID-19 disease and also deviation from planned delivery times was bigger due to testing drivers for COVID-19 infection on every border crossing. Based on related research, the supply chain losses related to initial COVID-19 virus pandemic lockdowns were largely dependent on the number of countries imposing restrictions and that losses were more sensitive to the duration of the lockdown than on the strictness. Stricter and shorter lockdowns could minimize overall losses. A "go-slow" approach to lifting restrictions may reduce overall damage if it avoids the need for further lockdowns (Lauri, 2020).

While it is essential to quickly adapt to sudden disruptions, it is necessary to take into account the efforts of customers and consumers to pre-supply food and other products during the onset of the Covid-19 virus pandemic crisis, which will in turn affect demand for these products once the situation returns to normal.,

In available time frame, mitigation of potential supply chain disruptions together with preventive, response and reactive measures are critical for economic, effective and efficient solutions. There is no rulebook for so wide disruptions on the global scale and scope, as due to COVID-19 virus pandemic or similar crisis. A resilient supply chain must be able to detect disruption early warning signs and respond by shifting production to alternative sources (Volkin, 2020). For this reason, appropriate approaches to the identification of future demand and availability of supply are crucial, for which appropriate forecasting methods and approaches are needed (Foltin, Brunclik, Ondryhal, & Vogal, 2018). Standard approaches and tools for logistics analysis are (Tang, Chung-Piaw, & Kwok Kee, 2008):

- Descriptive analytics to check out the past performance of the supply chain based on data mining to gather raw information from the supply chain;
- Predictive analytics to identify the possible future trends and test the potential scenarios;
- Prescriptive analytics to identify what could happen and how to deal with potential future scenarios;
- Performance metrics to properly identify the effectiveness and efficiency of adopted plans in comparison to the real results;

- Hybrid performance measurement, as a complex form of chain analysis, combining several methods based on the hierarchy of identified objectives.

It is possible to agree with Taleb that businesses (and supply chains in particular) should prepare themselves for unexpected events and be “antifragile” (AKIpress News Agency, 2020), but the question remains how many of them follow the advice? What should supply chains be prepared for? It is something that is hard to predict, has an impact which is unknown and will last for an unknown time. So, what are the necessary procedures for the elements of supply chains if they are struck by such an event? The presented research first summarized known forecasting methods of the demand and discussed their potential to react fast enough to the sudden changes in demand.

Main research question is the identification of the key aspects and possible applicable methodological approaches to predicting impacts of highly uncertain and further evolving COVID-type disruptions to supply chains and its elements.

4. METHODS FOR IDENTIFYING SUDDEN CHANGE

Traditional methods for forecasting based on the time-series show a time delay ("lag") behind the real course and at the same time they smooth past data (i.e. they reduce the weight/significance of any deviations from the average). Therefore, they deal with higher sales as extremes which is a right thing to do in the longer perspective as the time of disruption is over, however, this leads to suboptimal behaviour during the disruption. For the sake of identifying the sudden change, it is possible to use change-point detection methods, which were mainly developed in the field of signal processing. These methods are divided into two basic groups:

- Offline methods;
- Online methods.

The difference is that with the offline methods, it is possible to search for all the change-points in the given time series while the online methods, which were attempt to be identified in the research carried out, are based on the last data received and their signal changepoints. In supply chain, operation context is usually long (typically 1 day) for the time frame for new data to arrive, so it is possible to use both online and offline methods for change-point detection (Wambui, Waititu, & Anthony, 2015):

- PLR - Piece wise linear regression;
- PELT - Pruned exact linear time;
- MACD - Moving average convergence divergence.

By employing methods mentioned above, it is possible to benefit from being alerted with just a 1-day delay about the disruption, so the time to react is provided.

The Python library *Ruptures* which cover dynamic programming, PELT, Binary segmentation, Bottom-up segmentation and Window-based change point detection were used for the purpose of testing the methods mentioned above (Truong, Oudre, & Vayatis, 2020). The PELT method from the library was used as it has a linear computational cost.

A sample of the Stock-Keeping Units (SKUs) in the Czech retailer operations was tested to find out if an algorithm can find the change points in sales. Results can be seen in the following Figures 3 -7.

Figure 3. Sales of soap with change-point on 27 February 2020

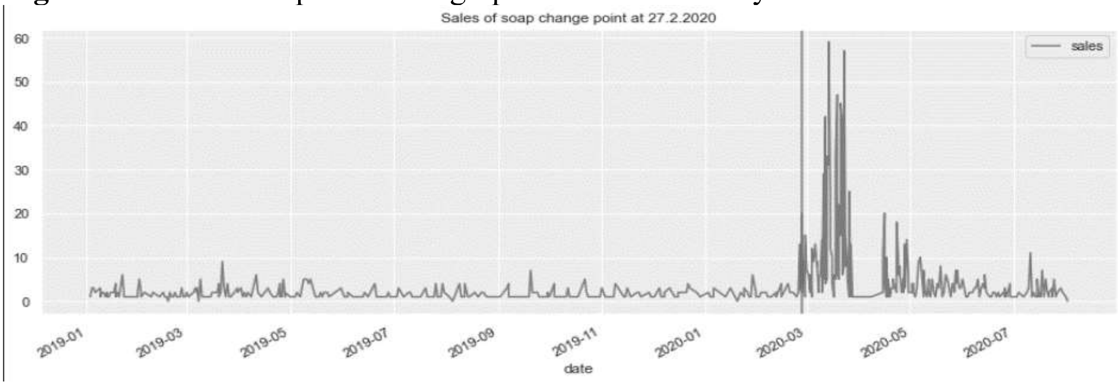

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Figure 4. Sales of potato mash with change-point on 26 February 2020

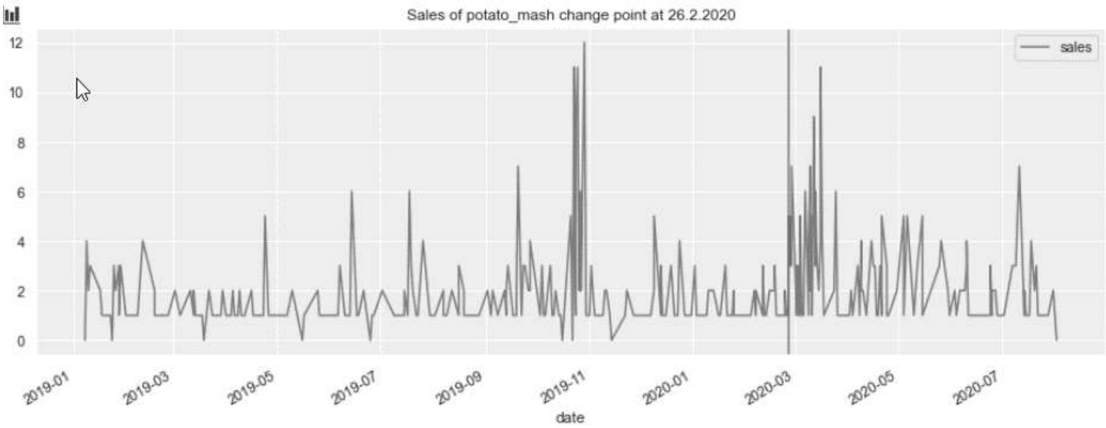

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Figure 5. Sales of rice with change-point on 26 July 2020

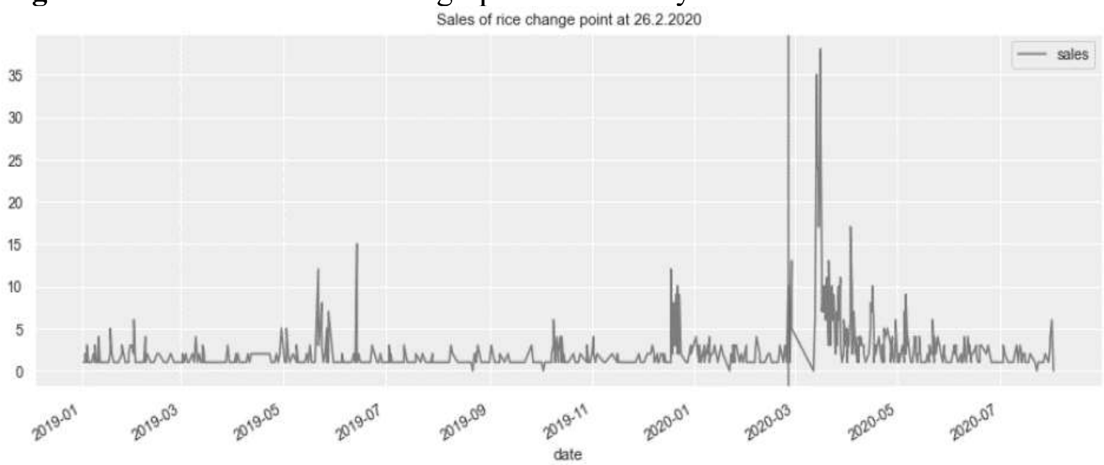

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Figure 6. Sales of whole grain flour with change-point on 13 March 2020

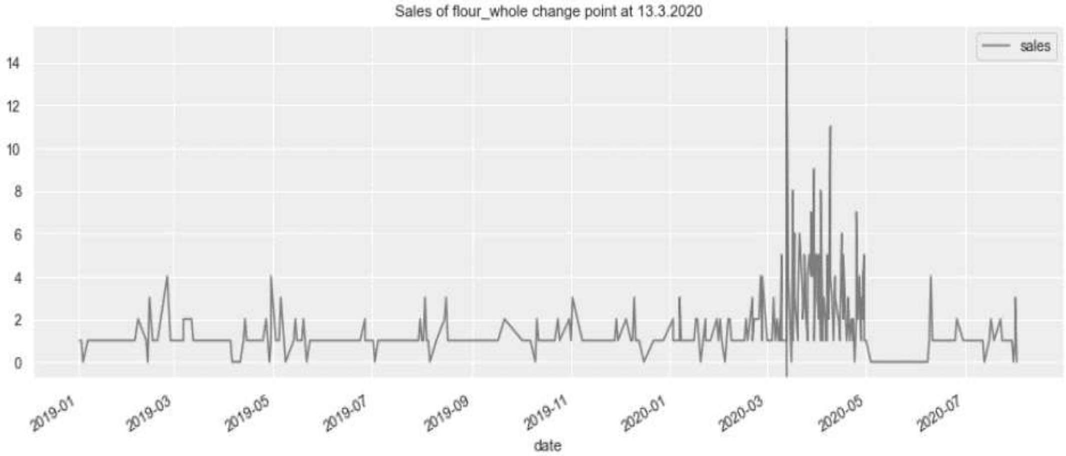

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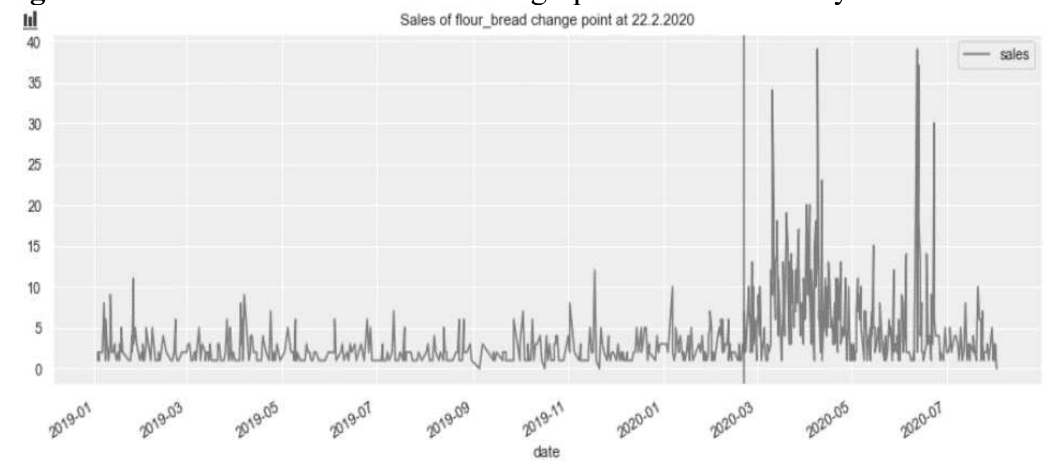
Figure 7. Sales of bread flour with change-point on 22 February 2020



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As can be seen in the chart, the sales increase corresponds to the news regarding COVID-19 virus pandemic spread in Europe. This happened approximately on the 26 February and followed with run on supermarkets.

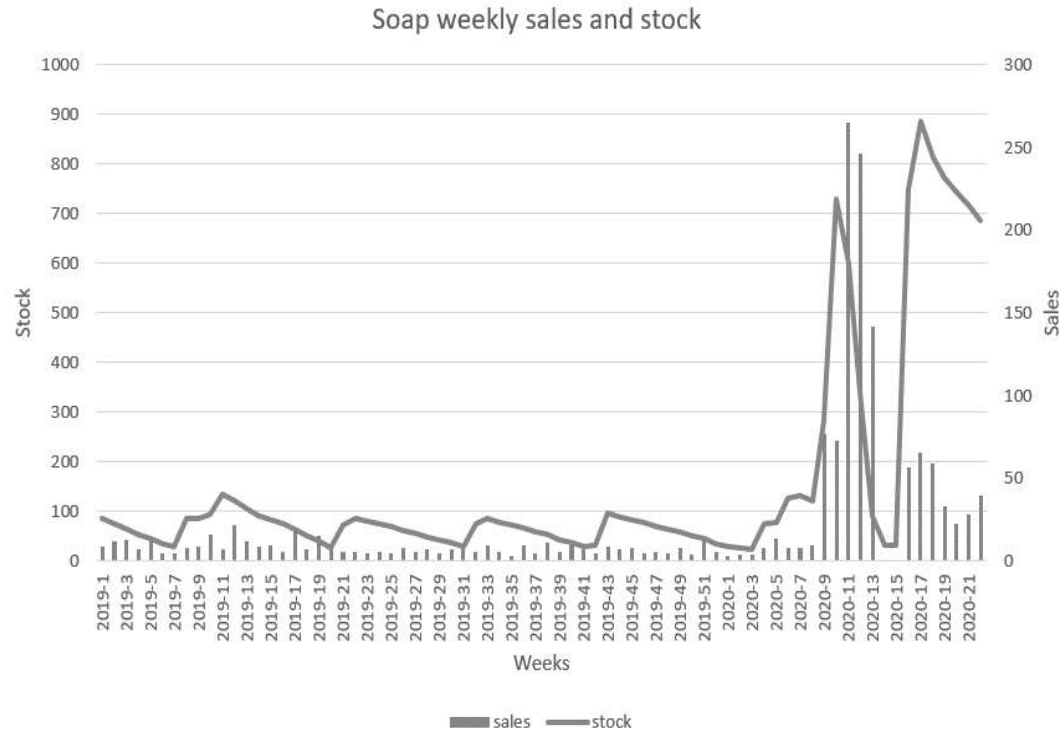
From Fig. 4 it can be seen that the algorithm can identify the change point even in the presence of past increase in sales in November 2019. It can also be noted, that this algorithm also found an increase in sale of rice (see Fig. 5), which was constrained by a limited supply.

5. DISCUSSION ON CHANGE UNDERSTANDING

When the change was identified, it was appropriate at first to understand what happened within the supply chain. First information was obtained from the data, regarding the fact whether the change was positive or negative. Negative change is more convenient from the point of view of the supply chain operations. It is possible just to wait until available stocks are depleted by decreased demand which obviously takes longer time. If the change is positive, it is necessary to understand what happened and estimate the shape of the future demand. It was possible to identify certain patterns in available data and bring a possible explanation based on the situation in the Czech Republic from the following charts (Figs. 8-12). Consumer behaviour can vary based on the culture and situation.

For the article of soap, shown in Fig. 8, the change point was identified on 27 February. It was possible to identify how the organisation selling this product reacted to increased demand by ordering stock which was not sold as the demand sharply decreased after two weeks of stock-outs. Start of the increased sales corresponds with the beginning of the first news regarding COVID-19 virus pandemic spread in Europe broadcasted in the Czech Republic.

Figure 8. Soap weekly sales and stock



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Customers also started accumulating long-lasting products, as shown in Fig. 9 with sales of rice. The organization reacted to the increased sales (and probably to the information from the media) and prepared itself for increased demand. However, they failed in the expectation that overall sales during this “stockpiling” period would finally lead to declining demand. It was possible to identify two distinct patterns of demand decrease: one in Fig. 9 and one in Fig. 10. In the case of rice, the demand decreased to previous levels, however, in the case of bread flour, it decreased only slightly, but stabilized on levels higher than before. The cause may be in the fact that with closed restaurants and overall lockdown in the Czech Republic which lasted to the half of May, people decided to prepare more food at their homes, which led to higher demand as people even started baking bread at home and some of them have continued with this even later.

Figure 9. Rice weekly sales and stock

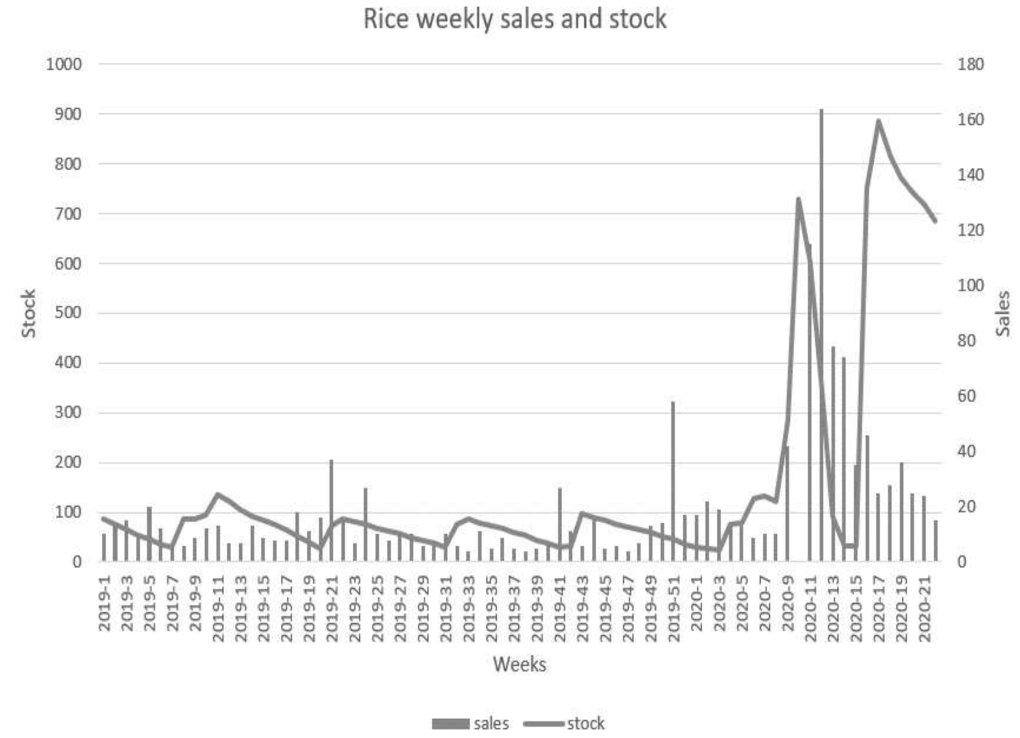

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Figure 10. Bread flour weekly sales and stock

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5.1. Beware of stockouts

The data about demand can be distorted by the failure to meet the demand in the situation when it increases suddenly. In Fig. 11, it is possible to identify that sales were limited by the available stock. This can lead to false observation that the demand decreased. The demand can still be present, however, due to insufficient stock, the information in the sales data is missing. It is remarkable that the organization tried to resupply the stores, however, probably too late and with an assumption that it would be as high as in the previous week. This led to the excess of the product inventory with a short expiration date: yeast in this particular case.

Figure 11. Yeast weekly sales and stock

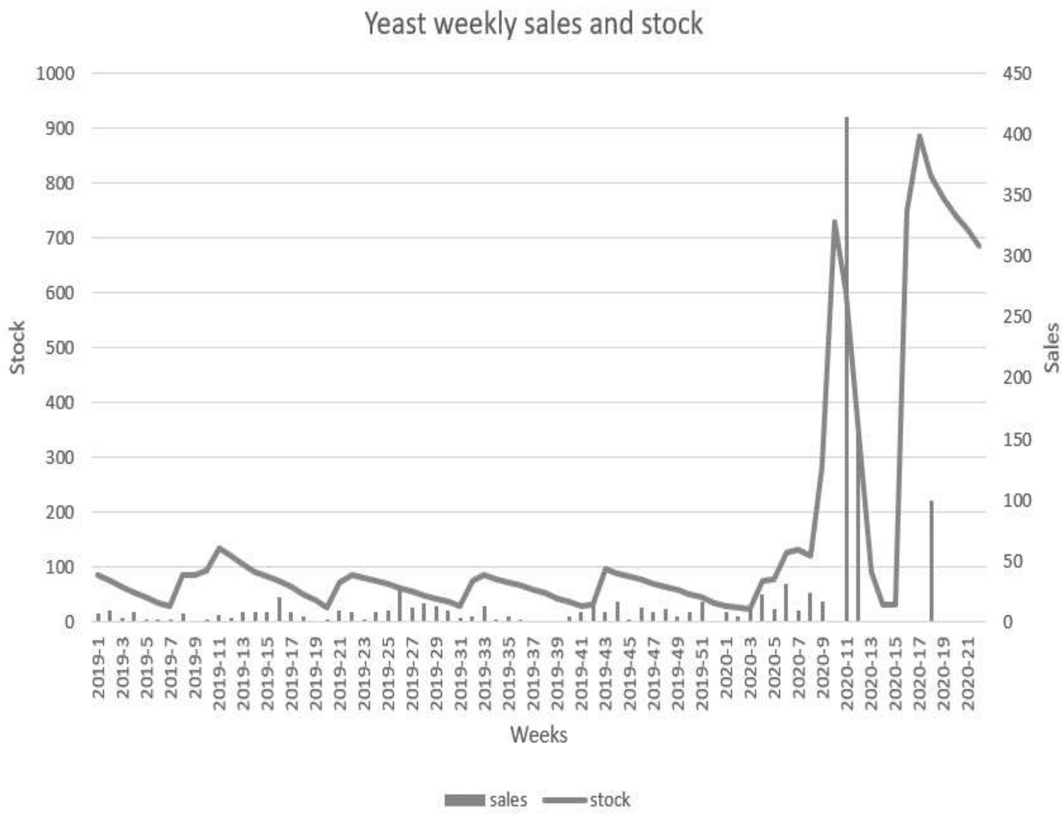

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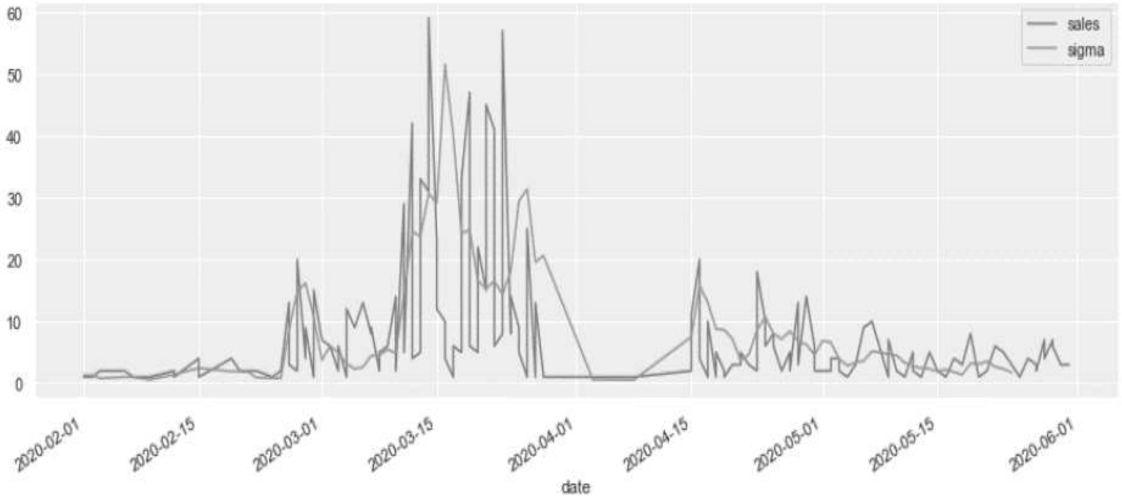
Figure 12. Forecast error and sales of soap



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It was necessary to evaluate the data of past sales together with the data of past inventory levels. Periods with no sales and zero (or very small) inventory levels were probably caused by unavailability of the product and the sales time series had to be adjusted with the estimate of lost sales. For this purpose, interpolation is often used.

5.2. Dealing with the change

For manually improving the forecast with limited hard data to create a forecast from a demand planner, two different approaches can be used. One is quite common and is based on a human guess making use of previous information the planners have. This can be the data from the market research or information available from the media or consideration based on announcement of measures defined by public administration. This can be only done in cases when a relatively small number of SKUs to forecast and/or enough demand planners to forecast them are available.

Adjusting safety stock if the organization has a system or process for forecasting should at least employ methods for dealing with the growing forecast error. Typically, the reorder point (ROP) is calculated as:

$$ROP = S * D_{LT}$$

where:

S … safety stock defined as

$$S = \sigma_F * SF$$

where:

σ_F … standard deviation of a forecast error

SF … service factor (an inverse normal cumulative distribution for a given service level)

D … forecasted demand for the given lead-time

When the σ_F is adjusted for a lead-time period, we receive a σ_L , then ROP can be calculated as:

$$ROP = D + \sigma_L * SF$$

It can be seen from Fig. 12 that when maintaining the forecasting method (in this particular case Holt-Winters exponential smoothing), the forecasting error increases as well as the calculated safety stock.

The system or process are set to automatically calculate the forecasted demand over the lead-time period and it automatically calculates also the error of forecast based on training data when the orders automatically increase due to increased safety-stock even if the forecast is not using the real data. What needs to be validated is the issue whether this approach does not lead to significant overstocking.

5.3. Going back to normal

Character of sudden changes in demand can differ. Some events in the history of mankind led to temporary changes in customer behaviour, where some of them can last for a long time or become permanent. It is therefore of the utmost importance to identify the end of such disruption. It is necessary for the forecasting process to mark the event and clean the time series from its effect. Same methods as described in the chapter 4 "Methods for identifying sudden change", can be used here.

6. CONCLUSION

The purpose of the research was to describe the situation of sudden demand changes in supply chains on examples related to the Czech Republic and explore the possibilities of currently available methods to deal with the sudden changes in demand. Suggestion for organizations dealing with the possibility of sudden change in demand, resulting from the research, can be described in five steps:

1. Employ forecasting models in the organization;
2. Make sure changes in demand are identified and reported;
3. Understand the causes of sudden demand changes and impact on investigated supply chain;
4. React to the demand changes and to identified impacts on supply chain;
5. Identify the end of the disruption and record the disruption as such for further forecasting process.

Forecasting based on time series data is widespread, but not a robust way to deal with sudden changes in demand. While there are many software programs on the market that promise to forecast the future, they only rely on the data and information that are provided to them. No "crystal ball" exists and it is unwise to expect software or methods to perform well in situations that did not happen in the past. Further research is recommended to evaluate methods for the identification of sudden changes and methods for rapidly changing forecasting methods used in the forecasting process. Still the first reaction of such software should be to alert its users that unexpected change is going to occur and which SKUs are going to be affected. The proposed method for evaluating a difference between the forecasted sales and actual sales data seems promising but further research should be dedicated to adjusting the parameters of such differences and testing it for both false positive and false negative results.

7. ACKNOWLEDGEMENT

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