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Analogous Forecasting of Products with a Short Life Cycle

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Abstract. Managing a supply chain for products with a short life cycle, like fashion apparel, high-tech, personal computers, toys, CD's etc., is challenging for many companies (Fisher and Raman, 1999). Because the life cycles of these products are too short for standard time-series forecasting methods (not longer than one – two years), an important way of overcoming the challenges of managing supply chains for such products is to find appropriate forecasting methodologies. The standard forecasting methods require some historical data, which are often unavailable at the time when the forecasts are being performed for products with a short life cycle (Lin, 2005). The method described in this article allows forecasters to use life cycles of similar, analogous products to arrive at the initial forecasts for the product(s) at hand.

Keywords: short life cycle, analogous forecasting, measure of similarity, calibrating, adjusting the length.

JEL Subject Classification: C1 – mathematical and quantitative methods/econometric and statistical methods: general, C19 – other.

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1. INTRODUCTION

The development of the market economy has brought about changes in the ways companies function. Consumer needs are growing. There are an ever-increasing number of information sources that are constantly developing. There's more competition, more products, technological and technical advances. That is why investors, especially entrepreneurs, are forced to change the behavior of companies in the marketplace. In order to maintain their positions in the market, companies have to become more flexible. They produce fewer products and need to adjust their production to fit the demand. The supply chain is "flattened" – the product has to reach the consumer in the shortest and the fastest way possible. This shortens the period for stocking any given product. The pace of increasing the sales and withdrawing the products from the market is faster. This situation is due to the great number of novelties appearing

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on the market. Despite the remarkable acceleration of the arrival of new products that compete with "old," companies are trying to maintain the quality of offered products and services. These qualities influence the interest in a given product; this interest is the definition of a product's life cycle, which usually does not last longer than two years.

Managing products with a short life cycle – like fashion apparel or technology products – is challenging for many companies. Because the life cycles of these products are too short for standard time-series forecasting methods (not longer than one-two years), one of the most important ways of overcoming the challenges of managing supply chains for such products is to find appropriate forecasting methodologies (Fisher and Raman, 1999). The standard forecasting methods require some historical data, which are often unavailable at the time when the forecasts are being performed for products with a short life cycle (Lin, 2005). The life cycle profiles for these products are different from profiles of a standard product life cycle. They have a high introduction spike, a gradual leveling-off of sales in the maturity phase, and then a swift decline in sales when a new generation of products is introduced (Wu and Aytac, 2007).

2. LITERATURE REVIEW

The forecasting problem of products with a short life cycle has been discussed in the literature in many different contexts. Several authors have used data-dependent forecasting methods: Harpaz, Lee and Winkler (1982), Azoury (1985), Duncan, Gorr and Szczypula (2001) use the Bayesian demand model. Johnson and Thompson (1975) and Ray (1982) model demand as an ARIMA process, Miller (1986) as an exponential smoothing formula. But we always have to remember that it is a forecast for a new product that we are after, and because of that have data from a limited period of time only or no data at all. This reality very often disqualifies statistics from these methods when trying to forecast sales for short life cycle products. New product forecasting is more than a technique: it is a process that needs to be properly managed (Kahn, 2006). The same is true for products with a short life cycle.

Some authors make entire life-cycle procurement decisions before any demand is realized or forecast updated. Kurawarwala and Matsuo (1995), Lin (2005) use the growth model. Fisher and Raman (1996, 1999) use heuristic methods in the field of Strategy Accurate Response. They suggest using the knowledge of experts to calculate forecasts for a new product, combining results and then deriving the most probable forecasts. Green and Armstrong (2007) describe an analogous system. This procedure involves five steps: describing the target situation, selecting experts, identifying and describing analogies, rating similarity, and at the end, deriving forecasts. Kahn (2002) suggests forecasting practices for new products during the commercialization stage, while Burruss and Kuettner (2002/2003) use forecasting by analogy before any demand is realized.

The concept of applying analogies has been explored not only in forecasting but also in many research fields, for example, in psychology, artificial intelligence and decision support. In psychology, it is termed 'pattern matching', and is found to be a basic component of many human cognitive models (Brzeziński et al. 1997) (Lindsay and Norman, 1977). In artificial intelligence, it is known as Case-based Reasoning (Lee and Goodwin, 2007). Nikolopoulos, Goodwin, Patelis, and Assimakopoulos (2007) used it to forecast TV audience ratings (in this application the process was referred to as 'nearest neighbor analysis'). Very often forecast by analogy is used to adjust statistical forecast in order to take into account special events (Lee, Goodwin, 2007).

In this article we present a forecasting model that can be applied when the sales history of products with a short life cycle are known for only a limited period of time. This model joins analogous forecasting with marketing. It could be used as an updated model. It helps companies compare sales of a new product with sales of similar products introduced earlier into the marketplace.

3. ANALOGOUS FORECASTING AND MEASURES OF SIMILARITY FOR TWO FUNCTIONS

Analogous forecasting is an efficient planning tool for products with a short life cycle from the same range of products. Analogous forecasting is defined as: "forecasting the future of a given variable by using information about other variables, with similar but not simultane-ous changes of time" (Cieślak et al. 2000).

Preparing a sales forecast by analogy requires finding analogies among variables, which is possible using measures of similarity of functions that enable stating whether sales quantities of compared products are similar. The measure of similarity described by Cieślak and Jasiński (1997) is remarkable. It is used for checking the similarity of the shape of compared objects.

It is applied in the following conditions:

(a) when functions f and g are given,

(b) when functions f and g are analyzed in ranges $[a, b]$ and $[c, d]$ then $b–a = d–c$,

(c) in the range $[a, b]$ points $a \leqslant a_1 \leqslant \cdots \leqslant a_n \leqslant b$ are analyzed, and in the range $[c, d]$ points $c \leqslant c_1 \leqslant \cdots \leqslant c_n \leqslant d$ are analyzed,

(d) we distinguish pairs of lines going through points $\{a_i, f(a_i)\}$ and $\{a_i + 1, f(a_i + 1)\}$ and $\{c_i, g(c_i)\}$ and $\{c_i + 1, g(c_i + 1)\}$,

(e) α_i is a measure of the angle created by two lines described in (d).

$$m_i = \begin{cases} 1 - \dfrac{2}{\pi}\alpha_i & \text{when functions } f \text{ and } g \text{ have the same monotonicity,} \\ -\dfrac{\alpha_i}{\pi} & \text{when functions } f \text{ and } g \text{ have different monotonicities.} \end{cases} \tag{1}$$

A similarity measure of functions f and g is determined by:

$$m = \frac{1}{n}\sum_{i=1}^{n} m_i \tag{2}$$

It can be proved that: $-1 < m \leqslant 1$.

The measure of angle α_i between lines going through specified points can be determined using one of the following formulas (Nowak et al. 1998):

$$\cos\alpha_i = \frac{(a_{i+1}-a_i)(c_{i+1}-c_i)+(f(a_{i+1})-f(a_i))(g(c_{i+1})-g(c_i))}{\sqrt{((a_{i+1}-a_i)^2+(f(a_{i+1})-f(a_i))^2)}\sqrt{((c_{i+1}-c_i)^2+(g(c_{i+1})-g(c_i))^2)}} \tag{3}$$

or

$$tg\alpha_i = \frac{\left(\frac{f(a_{i+1})-f(a_i)}{a_{i+1}-a_i}\right)-\left(\frac{g(c_{i+1})-g(c_i)}{c_{i+1}-c_i}\right)}{1+\left(\frac{f(a_{i+1})-f(a_i)}{a_{i+1}-a_i}\right)\left(\frac{g(c_{i+1})-g(c_i)}{c_{i+1}-c_i}\right)} \tag{4}$$

Positive values of measure mean that both series have similar shapes (with, for example, increasing or decreasing trends), negative values – mean the opposite. The closer the value of measure is to 1, the greater the similarity (Diettmann 2002).

The second similarity measure of compared products used in this article is Euclid Distance. It is used for checking the similarity of the value of compared objects.

4. TRANSFORMATION THE SALES SERIES OF SIMILAR PRODUCTS

When a product is introduced onto the market the following situation can be observed: a sum of sales quantity and the length of the life cycle of these products resemble a sum of sales quantity and a length of the life cycle of different products which were earlier introduced onto the market (Wu and Aytac, 2007). This phenomenon is shown in the Figure 1.

The shift of sales of product B backwards by 23 units (weeks) allows the observation of similarities in the life cycles of two products: A and B.

With this information about the initial sales of a new product, an analogous forecast can be calculated. We can calculate the similarity of a new product with analogous products introduced earlier to the market and chose a product that has the highest similarity in terms of sales figures.

In order to achieve a comparison as accurate as possible, we can modify the sales figures of the product introduced earlier to the market by: *calibrating* and/or *adjusting the length* of the figures being compared. Calibrating the figures changes the volume of sales being compared; while adjusting the length changes the amount of time being compared.

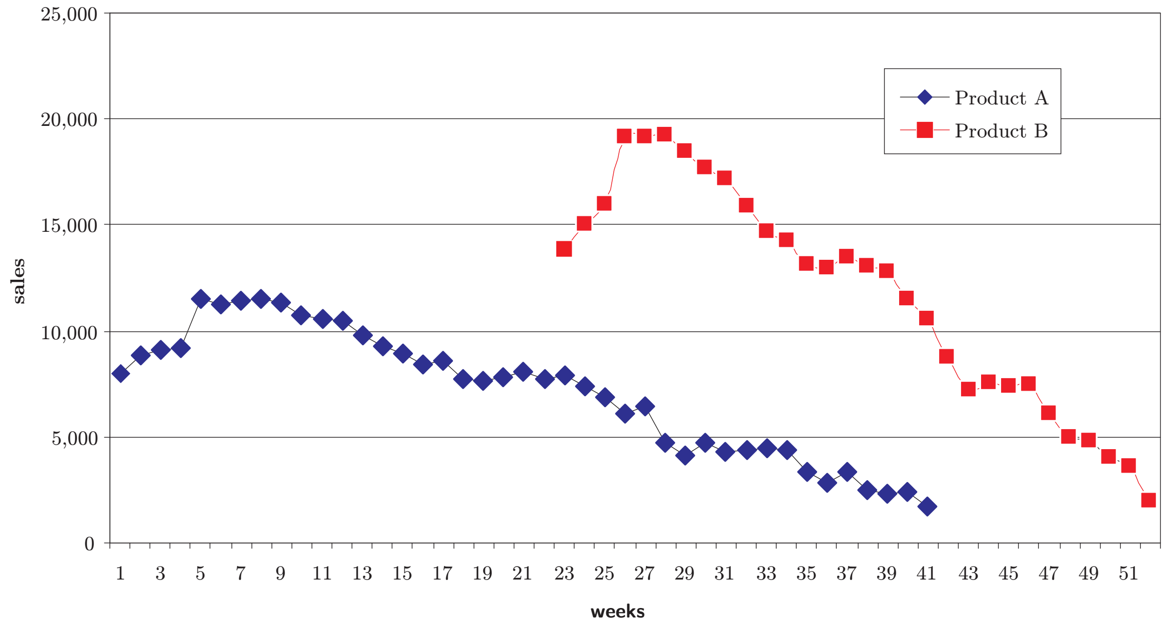


Fig. 1. *Life cycles of products A and B*

I Calibrating

Because sales of a new product could have a lower or higher volume than sales of sim-ilar products, those sales may need to be calibrated up or down. In this way the volumes of compared figures are adjusted.

Calibrating is done by applying the following procedure:

– Sales quantities $D_1, \ldots, D_k$ are given.

– Calibrating coefficient w is calculated.

– Calibrated volumes equal: $v_1, \ldots, v_k$:

$$\nu_k = w \cdot D_k \tag{5}$$

The value w is calculated to get a comparable volume for the analyzed time period. The calibrating coefficient can be either lower or higher than 1, with the assumption that $w > 0$.

II Adjusting the length

The length of time being compared can also be adjusted. The sales increase of a new product can be faster or slower over time when compared with a product that was introduced earlier onto the market. In either of these circumstances the range of one product being compared is changed.

Under this hypothesis one unit of time can be compared with a different, but analogous, unit of time. The matching parameter δ is used to transform the set of sales figures of similar products.

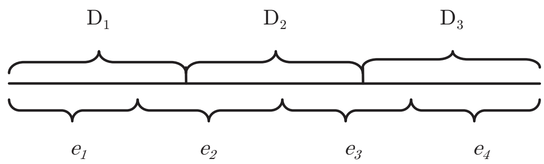
Adjusting the length is done by applying the following procedure:

a) $\delta < 1$

– Sales quantities D_1, D_2, D_3 are given.

– The matching parameter $\delta = 0.75$ is given as a part of unit of time.

– Aggregated volumes equal $e_1, \ldots, e_4$.



$e_1 = 0{,}75D_1$ $\qquad$ $e_3 = 0{,}5D_2 + 0{,}25D_3$

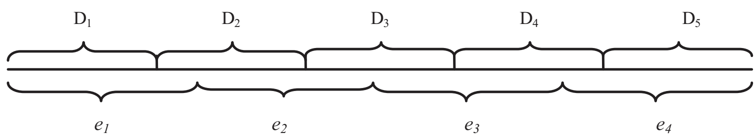
$e_2 = 0{,}25D_1 + 0{,}5D_2$ $\qquad$ $e_4 = 0{,}75D_3$

b) $\delta > 1$

– Sales quantities $D_1, \ldots, D_5$ are given.

– The matching parameter $\delta = 0,75$ is given as a multiplication factor of unit of time.

– Aggregated volumes equal $e_1, \ldots, e_4$.



$e_1 = D_1 + 0{,}25D_2$ $\qquad$ $e_3 = 0{,}5D_3 + 0{,}75D_4$

$e_2 = 0{,}75D_2 + 0{,}5D_3$ $\qquad$ $e_4 = 0{,}25D_4 + D_5$

Adjusting the length is done in order to lengthen or shorten the length of series representing sales over time of similar products. If the matching parameter is greater than 1 the length of time is shortened. If the matching parameter is less than 1 the length of time is made longer.

5. CALCULATING A FORECAST FOR A NEW PRODUCT

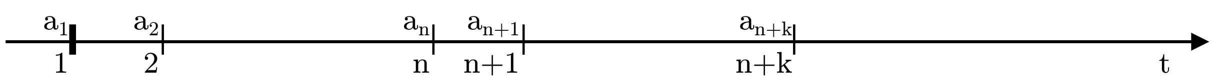
Analogous forecasting for a new product using similarities between comparable objects is possible when both the sales volumes of similar products (introduced earlier to the market) and initial sales figures for the new products are available. The Measure of Similarity by Cieślak, Jasiński and the Euclid Distance are used for this procedure. We check which sales of similar products have the highest similarity to the sales of the new product. The next step checks if calibrating or adjusting the length of the sales of the similar products improves similarity.

The steps leading to the final result, which is the forecasting of sales of the new product are presented below:

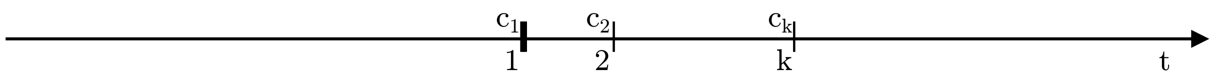
Sales volumes for products A and B are known, as historical data have been provided. Product C is a new product. The goal of this research is to answer the following question: Will sales of product C be more similar to the sales of product A or B? If the measure of similarity is acceptable, it will be possible to create a template to be used to calculate a forecast of sales for the new product C. If it is unacceptable, it will be necessary to check if calibrating or adjusting the length will increase the similarity between comparable time series.

I Calibrating

Sales data of product A $(a_1, \ldots, a_{n+k})$ and C in time series $n+1, \ldots, n+k$, C $(c_1, \ldots, c_k)$ are given.



Sales of product A



Sales of product C

Sales data for products A and C $((a_1, \ldots, a_k)$ and $(c_1, \ldots, c - k)$ for $k > 2)$ in first k time series is analyzed. In the first step of the analysis, calibrating coefficient w_k for every k is searched. It allows a change from time series $(a_1, \ldots, a_k)$ into time series $(v_1, \ldots, v_k)$:

$$v_i = w_k \cdot a_i, \qquad \text{with } i = 1, \ldots, k. \tag{6}$$

so as to calculate the similarity between sales of product A and C using function:

$$f_k = \frac{d_k^{(e)}}{m_k}, \tag{7}$$

where:

m_k – measure of similarity of both functions defined in (1) and (2),

$d_k^{(e)}$ – Euclid Distance defined by:

$$d_k^{(e)} = \frac{\sum\limits_{i=2}^{k} \sqrt{(c_{i-1} - v_{i-1})^2 + (c_i - v_i)^2}}{k-1} \tag{8}$$

Calibrating coefficient w_k^* is searched for:

$$f_k \to \min. \tag{9}$$

Calculated calibrating coefficient w_k^* is used to determine the sales forecast for product C for $k+1,\dots,k+n$ periods:

$$p_{k+i} = \hat{v}_{k+i} = w_k^* \cdot a_{k+i}, \qquad \text{with } i = 1,\dots,n. \tag{10}$$

II Adjusting the length

The second step is done in order to check the possibility of calculating a more accurate similarity between volumes of sales for products A and C, by using adjusting the length me-thodology. The basics of this adjustment are: modifying the time series for product A $(v_1,\dots,v_k)$ and the time series for product C $(c_1,\dots,c_k)$.

For time series $(v_1,\dots,v_k)$ the matching parameter δ_k, and transformation of the time series $(v_1,\dots,v_k)$ into time series $(e_1,\dots,e_r)$ when $r \geqslant k$, are calculated. To calculate the forecast time series, $(e_1,\dots,e_k)$ and $(c_1,\dots,c_k)$ are needed. Similarity is calculated by function f_k defined by formula (7). Quantity of matching parameter δ_k^* is searched for:

$$f_k \to \min . \tag{11}$$

When $\delta_k^* \neq 1$ the modified forecast for product C can be calculated. It is possible when time series $(v_1,\dots,v_{k+n})$ is transformed into time series $(e_1,\dots,e_{k+n})$ by using matching parameter δ_k^* . The forecast is defined:

$$p_{k+i} = e_{k+i}, \qquad \text{with } i = 1,\dots,n. \tag{12}$$

III Comparison of results

The same procedure (shown in I and II) is used for product B, and the similarity between sales of products B and C is calculated.

Received similarities are compared (between A and C or B and C) – the results for volume functions f_k are compared and the template with the lowest f_k is chosen.

Verification of results is done by calculating the forecast error for example MSE. For products with a short life cycle, forecasting is calculated for short periods. Thus, the following formula should be used:

$$MSE = \frac{\sum\limits_{k=1}^{n} (y_k - p_k)^2}{n-1} \tag{13}$$

6. EXAMPLE

The example presented below illustrates the application of the methodology to calculate a forecast for a new product. Sales volumes for similar products sold on different European markets (at the beginning of their life cycles) are known. Product Y is introduced onto the Polish market, and it is in the same range of products. Sales volume in two quarters of the year 2008 for the new product are known. A forecast for Poland in the third and fourth quarters of the year 2008 is calculated by using sales of similar products. Tables 1 and 2 represent sales of analyzed products.

Table 1. *Sales quantity for similar products on different markets [thousand of pieces]*

Country	the first year			
	1st quarter	2nd quarter	3rd quarter	4th quarter
Holland	442,176	83,702	263,434	271,300
Denmark	90,173	60,000	66,244	136,627
Finland	122,050	42,000	79,836	197,164
Sweden	6,754	44,400	211,897	275,729
Belgium	136,030	58,000	33,470	118,763
France	990,010	656,000	604,000	1,030,400
England	1,008,619	853,283	898,552	967,81
Luxemburg	11,289	0,000	25,117	16,146
Estonia	14,319	3,300	11,000	10,605
Spain	282,099	564,157	293,200	460,651
Portugal	94,658	58,000	133,532	24,909
Austria	181,825	55,900	108,230	57,407
Italy	526,257	211,000	444,270	828,279
Germany	624,856	351,567	532,753	2295,35
Slovenia	13,839	2,700	35,557	1,586
Ireland	17,132	16,100	35,600	59,834
Lithuania	28,110	13,458	26,674	36,763
Hungary	32,483	38,231	11,131	117,133
Czech Republic	19,049	43,659	87,95	173,141
Latvia	3,000	3,000	1,000	37,415
Slovakia	9,800	2,500	37,800	21,500
Greece	22,343	21,400	15,915	48,503

Table 2. *Sales quantities of the year 2008 for a new product in Poland [thousand of pieces]*

Country	1st quarter	2nd quarter
Poland	201,266	140,800

The first two quarters in sales of the new product are compared with and sales of similar products. The first transformation applied is calibrating. The best results will be obtained calibrating the coefficient with the lowest value function.

Table 3 presents a transformation for the time series of similar products, which is the base of the forecast for the new product.

Table 3. *Calibrating sales series for similar products*

Country	w_k – calibrating coefficient	ν_k – modified sales [thousand of pcs.]				f_k – value function
Holland	0.50	219,873	41,621	130,993	134,905	101.62
Denmark	**2.27**	**204,438**	**136,031**	**150,187**	**309,757**	**5.73**
Finland	1.83	223,198	76,807	145,999	360,561	68.07
Sweden	0.86	5,818	38,244	182,518	237,500	14,632.13
Belgium	1.63	221,054	94,252	54,390	192,995	50.86
France	**0.21**	**204,689**	**135,631**	**124,880**	**213,040**	**6.21**
England	0.19	186,770	158,006	166,389	179,214	22.76
Luxemburg	17.80	200,951	0,000	447,098	287,409	141.84
Estonia	15.49	221,792	51,115	170,383	164,264	92.63
Spain	0.29	80,696	161,380	83,871	131,771	13,275.65
Portugal	2,.21	209,046	128,089	294,897	55,010	14.94
Austria	1.23	223,338	68,663	132,940	70,514	75.93
Italy	0.42	221,969	88,997	187,387	349,358	56.11
Germany	0.34	213,030	119,858	181,630	782,545	24.11
Slovenia	15.91	220,192	42,960	565,745	25,235	100.35
Ireland	10.35	177,372	166,688	368,577	619,478	37.04
Lithuania	7.77	218,542	104,629	207,378	285,815	40.28
Hungary	4.49	145,744	171,534	49,942	525,551	3,603.90
Czech Republic	0.00	0,013	0,029	0,059	0,116	490.95
Latvia	57.01	171,033	171,033	57,011	2,133,067	4,264.62
Slovakia	22.71	222,570	56,778	858,483	488,291	87.26
Greece	7.86	175,686	168,271	125,142	381,385	40.57

The best results for the value functions are obtained when sales for a new product introduced onto the Polish market are compared with sales of a similar product in Denmark. Very similar results were calculated for France. The profile of sales in those two countries are the most similar to the profile of sales for product Y in Poland. Using calibrating it is possible to calculate a forecast $p_{k+1}^{(w)}$, with a value of 150,187 pieces, and $p_{k+2}^{(w)}$, with a value of 309,757 pieces. The results of calibrating are shown in Figure 2.

Sales figures in Sweden, Spain, Hungary, Czech Republic and Latvia are very different from the sales figures of a new product in Poland. Sales in these countries have a very high value function. This is the reason why these product figures are eliminated from the next step. The next step is checking if adjusting the length improves the result. Outcomes of adjusting the length of time series for similar products are presented in Table 4.

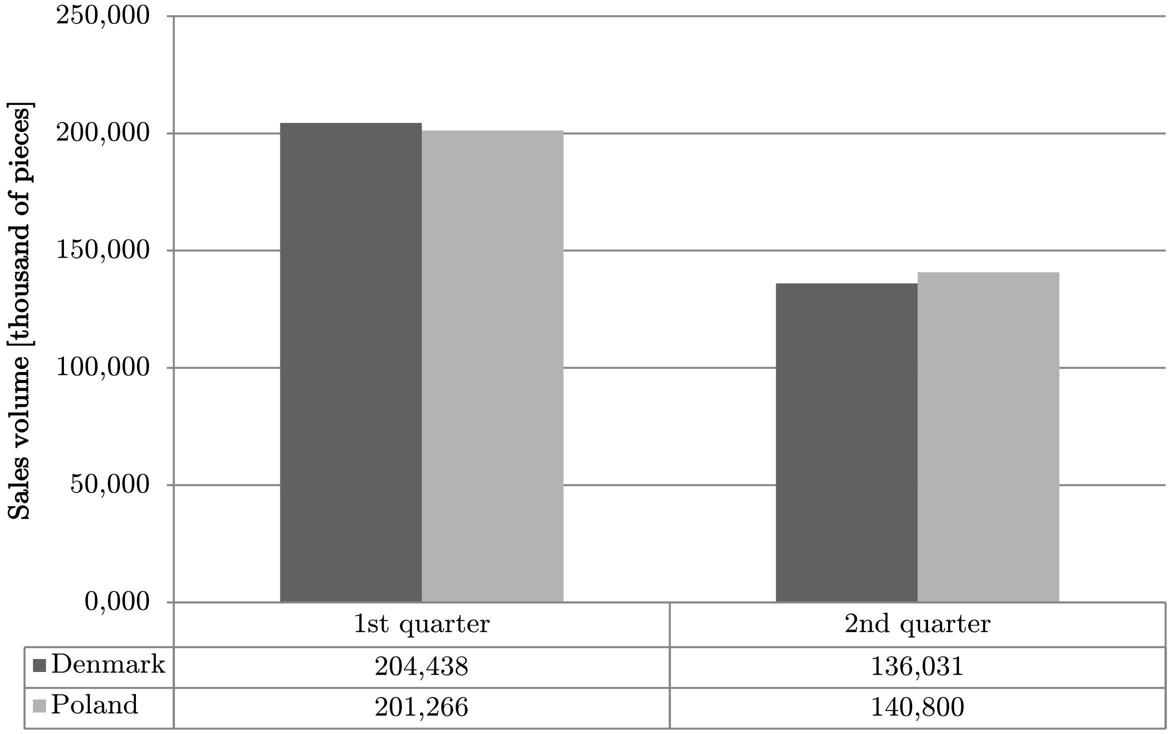


Fig. 2. *Sales volume of a new product Y on the Polish and modified sales of similar product on the Danish market*

Table 4. *Adjusting the length of sales series for similar products*

Country	δ_k – matching parameter	e_k – modified sales [thousand of pcs.]				f_k – value function
Holland	1.30	232,360	130,243	223,596	203,193	32.98
Denmark	**1.02**	**202,394**	**135,354**	**145,080**	**294,990**	**4.81**
Finland	1.40	253,920	144,464	400,975	290,726	53.03
Belgium	0.70	198,949	97,507	66,518	165,408	43.54
France	**0.99**	**202,642**	**134,965**	**1,369,330**	**230,766**	**6.00**
England	1.00	186,770	158,006	166,389	179,214	22.76
Luxemburg	1.30	200,951	125,547	204,756	189,542	15.29
Estonia	1.30	242,238	166,975	233,137	139,184	48.72
Portugal	1.00	209,046	128,089	294,897	55,010	14.94
Austria	1.30	243,937	127,828	116,639	81,355	44.83
Italy	1.10	230,868	117,575	254,717	403,895	37.81
Germany	1.10	225,016	144,199	380,067	946,220	24.06
Slovenia	1.10	224,487	151,813	460,167	27,663	25.75
Ireland	1.00	177,372	166,688	368,577	619,478	37.04
Lithuania	1.10	229,005	135,642	251,646	335,699	28.32
Slovakia	0.80	178,060	78,58071	366,104	612,7478	66.68
Greece	1.10	192,513	176,472	214,529	484,881	37.82

The results of value function f_k are again lowest for the Danish market. Using matching parameter δ_k which equals 0,96, the value function f_k is calculated and equals 4,81, which is a better result than in calibrating. Sales forecast $p_{k+1}^{(\delta)}$ and $p_{k+2}^{(\delta)}$ are changed and equal 145,080 and 294,990 pieces respectively.

The result of adjusting the length is demonstrated in Figure 3.

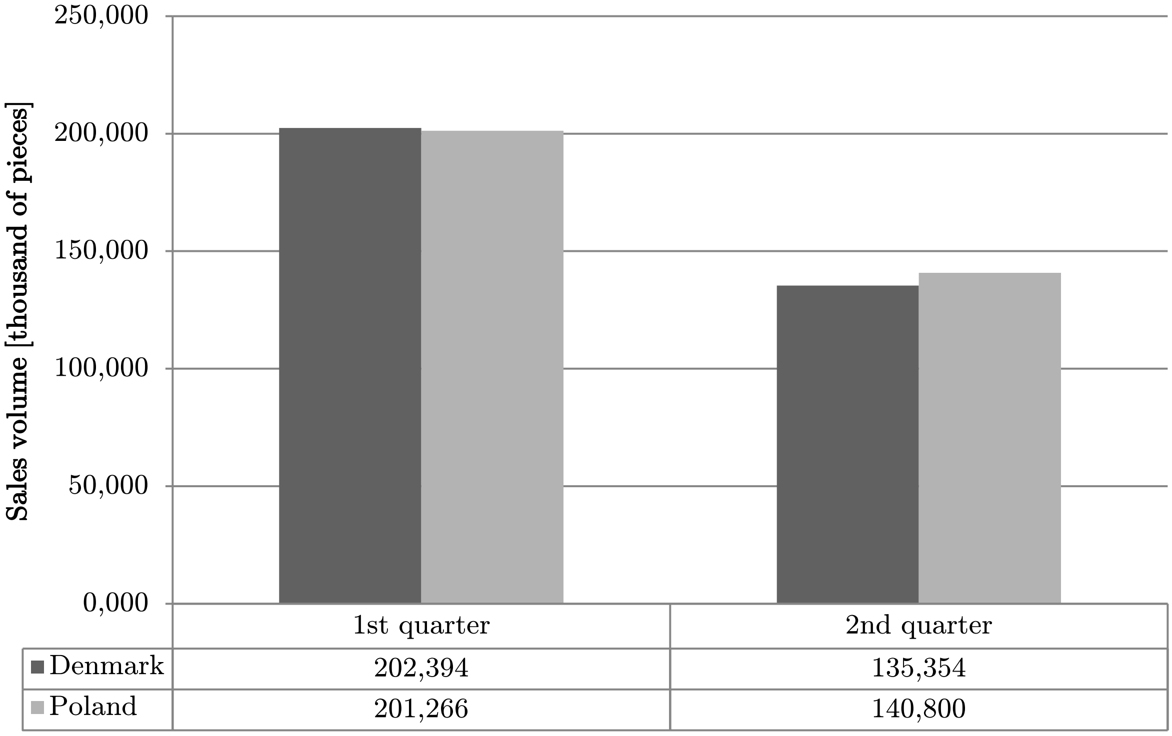


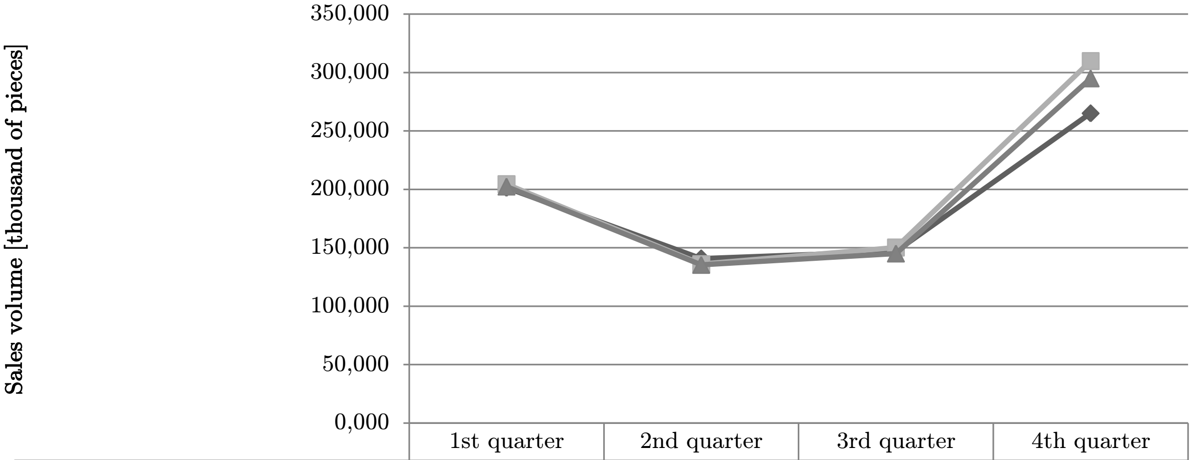
Fig. 3. *Sales volume of new product Y on the Polish market compared to a similar product on the Danish market after adjusting the length of time for sales being compared*

A very good result was also obtained after comparing our product with a similar product introduced into the French market. But our forecast is based on the modified sales of a similar product introduced into the Danish market.

Summary of the analysis is presented in Table 5 and Figure 4.

Table 5. *Comparison of sales forecasts for product Y [thousand of pieces]*

I	1	2	MSE
y_{k+i}	146,901	265,128	
$p_{k+1}^{(w)}$	150,187	309,757	2002,582
$p_{k+1}^{(\delta)}$	145,080	294,990	895,075



	1st quarter	2nd quarter	3rd quarter	4th quarter
Sales product Y into the Polish market	201,266	140,800	146,901	265,128
Forecast by using calibrating	204,438	136,031	150,187	309,757
Forecast by using calibrating and adjusting the length	202,394	135,354	145,080	294,990

Fig. 4. *Comparison of sales forecasts for product Y*

We can observe that this procedure allows for the calculation of a forecast with a very small forecast error.

7. CONCLUSIONS

This research leads us to believe that the hypothesis that measures of similarity, especially function f_k, can be used to calculate sales forecasts with only a small amount of data about sales for products with short life cycles. Repeated use of the presented methodologies enabled the determination of the following forecasting stages:

1) Checking the similarity between compared products using time series representing the sales life cycles of different products.
2) Transforming the sales data of similar, but different, objects by applying the methodologies of calibrating and adjusting the length.
3) Choosing the template that becomes the basis for calculating the forecast of sales for a new product for the whole life cycle.
4) Updating the forecast by calculating a part of a sales profile after receiving more data about sales of a new product (adapting process).

The presented methodology is not a perfect method of forecasting. However, it can be used not only for products with a short life cycle, but also for telecommunication services, new technologies, textile sales, etc. This forecast method allows the derivation of results with less than a 10% forecast error.

Despite the lack of historical data about sales for a new product, forecasting for their sales becomes possible. The presented example proves the effectiveness of analogous fore-casting for products that have a life cycle not longer than two years. Statistical methods are insufficient and less accurate in predicting sales for such products.

Having received accurate forecast data, product managers can make better decisions concerning coordination of logis-tical processes in companies.

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