Analogous Forecasting of Products with a Short Life Cycle

Natalia Szozda

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.


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 Assimakopoulous (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 simultaneous 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 $a \leq a_1 \leq \cdots \leq a_n \leq b$ are analyzed, and in the range $[c, d]$ points $c \leq c_1 \leq \cdots \leq c_n \leq d$ 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) $\alpha_i$ is a measure of the angle created by two lines described in (d).

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

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

$$m = \frac{1}{n} \sum_{i=1}^{n} m_i \quad (2)$$
It can be proved that: \(-1 < m \leq 1\).

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

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

(3)

or

\[
tg \alpha_i = \frac{(f(a_{i+1}) - f(a_i))}{a_{i+1} - a_i} - \frac{(g(c_{i+1}) - g(c_i))}{c_{i+1} - c_i}
\]

\[
1 + \left(\frac{f(a_{i+1}) - f(a_i)}{a_{i+1} - a_i}\right)\left(\frac{g(c_{i+1}) - g(c_i)}{c_{i+1} - c_i}\right)
\]

(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.
Calibrating

Because sales of a new product could have a lower or higher volume than sales of similar 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: \( v_1, \ldots, v_k \):

\[

v_k = w \cdot D_k

\]  

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 $\delta$ 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 $e_1, \ldots, e_4$.

   \[
   e_1 = 0.75D_1 \quad e_2 = 0.5D_2 + 0.25D_3 \\
   e_3 = 0.25D_1 + 0.5D_3 \quad e_4 = 0.75D_3
   \]

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 $e_1, \ldots, e_4$.

   \[
   e_1 = D_1 + 0.25D_2 \quad e_2 = 0.5D_1 + 0.75D_4 \\
   e_3 = 0.75D_2 + 0.5D_3 \quad e_4 = 0.25D_3 + D_5
   \]

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

\[
\begin{array}{cccc}
1 & 2 & \cdots & n+k \\
\hline
a_1 & a_2 & \cdots & a_n \\
& & \cdots & \\
& & \cdots & a_{n+k}
\end{array}
\]

Sales of product C

\[
\begin{array}{cccc}
1 & 2 & \cdots & k \\
\hline
& & \cdots & c_1 \\
& & \cdots & c_2 \\
& & \cdots & c_k
\end{array}
\]

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 \((v_1, \ldots, v_k)\):

\[
v_i = w_k \cdot a_i, \quad \text{with } i = 1, \ldots, k. \tag{6}
\]

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

\[
f_k = \frac{d^{(e)}}{m_k}, \tag{7}
\]

where:
- \(m_k\) – measure of similarity of both functions defined in (1) and (2),
- \(d^{(e)}_k\) – Euclid Distance defined by:

\[
d^{(e)}_k = \frac{\sum_{i=2}^{k} \sqrt{(c_i-1 - v_{i-1})^2 + (c_i - v_i)^2}}{k - 1} \tag{8}
\]

Calibrating coefficient \(w^*_k\) is searched for:

\[
f_k \rightarrow \min. \tag{9}
\]
Calculated calibrating coefficient \( w_k^* \) is used to determine the sales forecast for product C for \( k + 1, \ldots, k + n \) periods:

\[
p_{k+i} = \hat{v}_{k+i} = w_k^* \cdot a_{k+i}, \quad \text{with } i = 1, \ldots, n.
\] (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 methodology. The basics of this adjustment are: modifying the time series for product A \((v_1, \ldots, v_k)\) and the time series for product C \((c_1, \ldots, c_k)\).

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

\[
f_k \rightarrow \min.
\] (11)

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

\[
p_{k+i} = e_{k+i}, \quad \text{with } i = 1, \ldots, n.
\] (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:

\[
MSE = \frac{\sum_{k=1}^{n} (y_k - p_k)^2}{n - 1}
\] (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**

<table>
<thead>
<tr>
<th>Country</th>
<th>the first year</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1(^{st}) quarter</td>
</tr>
<tr>
<td>Holland</td>
<td>442,176</td>
</tr>
<tr>
<td>Denmark</td>
<td>90,173</td>
</tr>
<tr>
<td>Finland</td>
<td>122,050</td>
</tr>
<tr>
<td>Sweden</td>
<td>6,754</td>
</tr>
<tr>
<td>Belgium</td>
<td>136,030</td>
</tr>
<tr>
<td>France</td>
<td>990,010</td>
</tr>
<tr>
<td>England</td>
<td>1,008,619</td>
</tr>
<tr>
<td>Luxembourg</td>
<td>11,289</td>
</tr>
<tr>
<td>Estonia</td>
<td>14,319</td>
</tr>
<tr>
<td>Spain</td>
<td>282,099</td>
</tr>
<tr>
<td>Portugal</td>
<td>94,658</td>
</tr>
<tr>
<td>Austria</td>
<td>181,825</td>
</tr>
<tr>
<td>Italy</td>
<td>526,257</td>
</tr>
<tr>
<td>Germany</td>
<td>624,856</td>
</tr>
<tr>
<td>Slovenia</td>
<td>13,839</td>
</tr>
<tr>
<td>Ireland</td>
<td>17,132</td>
</tr>
<tr>
<td>Lithuania</td>
<td>28,110</td>
</tr>
<tr>
<td>Hungary</td>
<td>32,483</td>
</tr>
<tr>
<td>Czech Republic</td>
<td>19,049</td>
</tr>
<tr>
<td>Latvia</td>
<td>3,000</td>
</tr>
<tr>
<td>Slovakia</td>
<td>9,800</td>
</tr>
<tr>
<td>Greece</td>
<td>22,343</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Country</th>
<th>1(^{st}) quarter</th>
<th>2(^{nd}) quarter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poland</td>
<td>201,266</td>
<td>140,800</td>
</tr>
</tbody>
</table>

The first two quarters in sales of the new product are compared with 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

<table>
<thead>
<tr>
<th>Country</th>
<th>$w_k$ – calibrating coefficient</th>
<th>$\nu_k$ – modified sales [thousand of pcs.]</th>
<th>$f_k$ – value function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Holland</td>
<td>0.50</td>
<td>219,873</td>
<td>130,993 134,905 101.62</td>
</tr>
<tr>
<td><strong>Denmark</strong></td>
<td><strong>2.27</strong></td>
<td><strong>204,438</strong></td>
<td><strong>150,187 309,757 5.73</strong></td>
</tr>
<tr>
<td>Finland</td>
<td>1.83</td>
<td>223,198</td>
<td>145,999 360,561 68.07</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.86</td>
<td>5,818</td>
<td>130,993 134,905 101.62</td>
</tr>
<tr>
<td>Belgium</td>
<td>1.63</td>
<td>221,054</td>
<td>94,252 54,390 192,995 50.86</td>
</tr>
<tr>
<td><strong>France</strong></td>
<td><strong>0.21</strong></td>
<td><strong>204,689</strong></td>
<td><strong>104,880 213,040 6.21</strong></td>
</tr>
<tr>
<td>England</td>
<td>0.19</td>
<td>186,770</td>
<td>158,006 166,389 179,214 22.76</td>
</tr>
<tr>
<td>Luxemburg</td>
<td>17.80</td>
<td>200,951</td>
<td>0,000 447,098 287,409 141.84</td>
</tr>
<tr>
<td>Estonia</td>
<td>15.49</td>
<td>221,792</td>
<td>51,115 170,383 164,264 92.63</td>
</tr>
<tr>
<td>Spain</td>
<td>0.29</td>
<td>80,696</td>
<td>83,871 131,771 13,275.65</td>
</tr>
<tr>
<td>Portugal</td>
<td>2.21</td>
<td>209,046</td>
<td>128,089 294,897 55,010 14.94</td>
</tr>
<tr>
<td>Austria</td>
<td>1.23</td>
<td>223,338</td>
<td>68,663 132,940 70,514 75.93</td>
</tr>
<tr>
<td>Italy</td>
<td>0.42</td>
<td>221,969</td>
<td>88,997 187,387 349,358 56.11</td>
</tr>
<tr>
<td>Germany</td>
<td>0.34</td>
<td>213,030</td>
<td>119,858 181,630 782,545 24.11</td>
</tr>
<tr>
<td>Slovenia</td>
<td>15.91</td>
<td>220,192</td>
<td>42,960 565,745 25,235 100.35</td>
</tr>
<tr>
<td>Ireland</td>
<td>10.35</td>
<td>177,372</td>
<td>166,688 368,577 619,478 37.04</td>
</tr>
<tr>
<td>Lithuania</td>
<td>7.77</td>
<td>218,542</td>
<td>104,629 207,378 285,815 40.28</td>
</tr>
<tr>
<td>Hungary</td>
<td>4.49</td>
<td>145,744</td>
<td>171,534 49,942 525,551 3,603.90</td>
</tr>
<tr>
<td>Czech Republic</td>
<td>0.00</td>
<td>0,013</td>
<td>0,029 0,059 0,116 490.95</td>
</tr>
<tr>
<td>Latvia</td>
<td>57.01</td>
<td>171,033</td>
<td>171,033 57,011 2,133,067 4,264.62</td>
</tr>
<tr>
<td>Slovakia</td>
<td>22.71</td>
<td>222,570</td>
<td>56,778 858,483 488,291 87.26</td>
</tr>
<tr>
<td>Greece</td>
<td>7.86</td>
<td>175,686</td>
<td>168,271 125,142 381,385 40.57</td>
</tr>
</tbody>
</table>

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

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

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

![Figure 3](image)

**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]**

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>1</th>
<th>2</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>( y_{k+i} )</td>
<td>146,901</td>
<td>265,128</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( p_k^{(w)} )</td>
<td>150,187</td>
<td>309,757</td>
<td>2002,582</td>
<td></td>
</tr>
<tr>
<td>( p_k^{(\delta)} )</td>
<td>145,080</td>
<td>294,990</td>
<td>895,075</td>
<td></td>
</tr>
</tbody>
</table>
Analogous Forecasting of Products with...

Sales product Y into the Polish market

<table>
<thead>
<tr>
<th></th>
<th>1st quarter</th>
<th>2nd quarter</th>
<th>3rd quarter</th>
<th>4th quarter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales</td>
<td>201,266</td>
<td>140,800</td>
<td>146,901</td>
<td>265,128</td>
</tr>
<tr>
<td>Forecast by using calibrating</td>
<td>204,438</td>
<td>136,031</td>
<td>150,187</td>
<td>309,757</td>
</tr>
<tr>
<td>Forecast by using calibrating and adjusting the length</td>
<td>202,394</td>
<td>135,354</td>
<td>145,080</td>
<td>294,990</td>
</tr>
</tbody>
</table>

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 forecasting 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 logistical processes in companies.

REFERENCES
