PRACTICAL BUSINESS MODEL FOR SEASONAL DEMAND FORECAST AND ESTIMATION OF OPTIMAL ORDER QUANTITY IN FOREIGN TRADE MANAGEMENT

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Abstract: In the project of improvement and computerization of ordering high-quality women's classic tights imported from Italy, a specific business model was developed and implemented. It takes only objective parameters (like sizes and thickness) into account and might be applied to other imported goods with seasonal variations in historical sales data, to be taken as the approximation of actual demand data. Testing seasonal time-series forecasting models proved Holt-Winter's Multiplicative smoothing method (incorporating a trend component) to be the best method for all four sizes and majority of thickness categories. To determine optimal order quantities for future monthly orders, the newsvendor model was included, balancing the overage and underage costs. Due to the high critical ratio and as it turned out to be more expensive to lose a sale of any pair of tights than to have it in left-over inventory, the expected-profit maximizing order quantities tend to be larger than expected demand.

Key words: imports management, seasonal demand, forecasting method, optimal order, newsvendor model.

1. ORDERING AS ONE OF CRUCIAL PROBLEMS IN IMPORTS MANAGEMENT

Ordering problems arising in retail business tend to repeat and to be (due to the larger scale) even more profound *on the wholesales level* of the distribution channel, *especially in imports management,*where higher costs owing to transport modes and distance, delivery time *and* customs *impose* need for *matching supply with demand.* The goals of the project done for one Serbian import company[3] were to:

- improve and computerize the ordering process in order to enable and start forecasting future demand,
- put the system of registering and tracking sales in the function of effective and efficient ordering, and
- modify it so as to make demand forecast the sound basis of the financial planning and management.

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This company is an importer and wholesaler of high-quality hosiery and underwear imported mostly from Italy.[4] Women's hosiery, as a segment *of* its imports, includes: *classic tights*[5] (without pattern), fashion tights (with some pattern, i.e. printed or texture design), and other hosiery (like fishnet tights, stockings, socks, and knee-highs). The natural focus of this project and conducted research was on the classic tights, *representing* on average *77.12 % of total hosiery sales* in the observed five years period. Beside a number of different manufacturers and colors (which they name differently)[6], that may be abstracted, there are two basic objective parameters[7] for ordering classic tights: size and thickness. Tights *sizes correspond to* certain intervals of the consumers' height and weight and are related to the *physical constitution of a woman,* which is relatively stable in the course of time (in spite of efforts to gain or lose a few pounds). So, based on the same 60 monthly observations, we estimated the average proportion among sizes in the total volume of classic-tights sales to be: *17.34 % of size 1/2, 38.79 % of size 3, 34.27 % of size 4, and 9.59 % of size 5/6.*[8] But one cannot rely upon these percentages, being just means, because actual monthly figures vary around them or, statistically – deviate from them.

The second *tights'* main feature, *thickness is measured and expressed in denier* (in Italian abbreviated as DEN), being a gauge of yarn they are knitted of. Their thickness and type of yarn they are made of determine whether tights will be *sheer, semi-opaque or opaque.* You can see the difference between 7 and 70 den, but between 15 and 20 den – only under microscope. We tried to make a *classification of classic tights by their thickness to: thin (from 7 to 30 den),* sold all the year round (what could explain the fact that the most sold of all classic tights are those of 15 and 20 den), *medium (of 40 and 50 den), and thick (from 60 to 100 den and over),* wanted mostly in late autumn and winter. It does not mean that large quantities of thin tights may not be sold in the middle of the winter, for example, on account of New Year's Eve. Nevertheless, according to average figures, the highest level of demand for 7 and 8 den is before summer, in May, but it is not surprising that most of 15 den tights are sold in October. Although several factors may influence the choice of tights thickness, it is probably most significantly correlated to environmental, considering actual weather, season of the year, and climate in the region.

With all those problems: how many of which to order and sell, when and how, one might ask why the purchase manager does not order e.g. a hundred thousand pairs of tights, in accordance with last year's sales plus 20 %, just in case. He cannot do that, not only because of the habit of ordering monthly, bad as most other habits, but for some other reasons, too. Although there is no „use before" date on their packages, like youghourt's, tights are perishable and lose their quality as time passes. They even smell when they are fresh. They may also go out of fashion. So, it would be best if they were produced, sold, worn, and torn within one year. It does not mean they have to be discounted at the end of the season, just to get rid of them. They can wait on the shelves in the summer and be sold next season, but we cannot afford having capital tied up in left-over inventory. Moreover, due to the capital constraint, the company is unable to order a quantity for the whole year. In months with low demand for classic tights it is compensated with higher level of sales of other hosiery, underwear and swimming costumes. In that way, the variations in the value of monthly sales as well as monthly orders are amortized, so that money invested may remain approximately the same. And when it is not enough, there is a bank just across the street. Finally, some of the company's Italian suppliers prefer monthly orders. *With present turnover, replenishment opportunities, and capital available they simply have to make monthly orders.*

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4 Too long period of *low-quality domestic production* of hosiery created public opinion that only imported may boast of high quality, being not true. Since recently, Italian manufacturers are obliged to declare their products with "Made in Italy" label.

5 UN classifies together "panty hose and tights, of synthetic fibres, of wool or fine animal hair, of cotton and of other textile materials, knitted or crocheted". Although terms panty hose or pantihose and tights are sometimes used alternatively, we find more precise term *tights, as a close fitting (usually women's) undergarment covering the lower part of the body and the legs.*

6 And subjective parameters – model and design (being a matter of taste and difficult to measure) in the case of fashion tights.

7 Determined mostly by one factor, which is an objective circumstance and its impact can be relatively easily quantified.

8 Sizes 1 and 2 as well as 5 and 6 are usually combined. Even if they exist separately, they are calculated within these figures.

2. PREVIOUS, EXPERIENCE-BASED ORDERING PROCEDURE & NEED TO IMPROVE IT

Having experience in ordering for its retail stores, the company's purchase manager 'felt' that the most items they were selling were of size 3, then of size 4, much less of size 1/2, and finally the least of size 5/6. He made his own approximation for easier and faster ordering, taking ten items of sizes 1/2 – 3 – 4 – 5/6 *in the proportion 2:4:3:1.* On the one hand, *ordering too little of* any size *meant* not having enough goods and being unable to satisfy potential customers. The consequence would be the *loss of revenue* if there were no substitute to offer them. To prevent such situations, one may try to have an appropriate alternative for any item, whenever it is possible. On the other hand, *ordering too much implies opportunity costs due to excessive stock* and possible lack of working capital needed for other purchases, owing to tying up the capital in the stock the company might not need at all in near future.

Both cases *may have negative impact on profitability.* Need to repay old debts stresses deficiency of capital. It is also wise to have somewhat larger stock within one's financial capacity, at least of most frequently sold and deficient items. Even foreign wholesalers often run out of certain items as they do not foresee nor invest in such buffer inventory. Nevertheless, it was not too hard to make orders for this importer, as this company had the *accounting computer program tracking sales* in many details. It was the first and, until a few years ago, the only company in this branch with a program of that kind.

Before preparing an order, the purchase manager had to find out expected time of delivery and define the interval between that delivery and the next one, to determine the period for which he should order and provide sufficient goods. Then he printed out past sales data for the same period last one or two years as well as present inventory data. *Difference between past sales and present inventory roughly was the quantity to order.* He would intervene with any necessary corrections, usually upwards if he expected an increase in sales. He had also to round off quantities and adjust them to the standardized number of units in commercial[9] and transport packages. In spite of purchases from both wholesalers and tights producers, he could get *reports with past sales data for any period* only *by the producer.*[10] Further classification included models of tights manufactured by chosen producer. *Names of classic-tights models usually contain their thickness in denier.*[11] Those sales lists had the following columns: item, its five-digit code, quantity sold at defined period of time in units, value of that sales, current selling price, and inventory in units on the last day of defined period. Most of classic-tights models were further broken down. *Combined criteria* for it *were color and size.*[12] It could not be applied only to a few models without bar code. They caused problems at the beginning, because one had to make an inventory of them every time he made an order. Having been allocated new codes for each combination of size and color later on, it was possible to continue tracking their sales normally, by color and size.

The company had seldom an inventory shortage due to demand-supply mismatch, and inventory rarely hit zero in monthly sales reports. As we did not have records for actual demand, but only for actual sales, we had to approximate demand with sales and *use* those *actual sales data as the approximation of historical demand data.* So, in this research, historical sales data are used, as being only available, *to construct a forecast of expected demand.* It would have been better if the data on actual demand had been registered and maintained, to make a forecast of expected demand (as the mean) and its variability about the forecast, captured by its standard deviation. To enable it in the future, *the company should:*

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[9] There are usually *six pairs* of tights in commercial packages, and very rarely three, five or twelve.

[10] Sanpellegrino, Meri, Glamour, Pompea, Golden Lady, Omsa, Filodoro, Tre Orsi, Elledue, Azira, Aris, Bellissima, etc.

[11] For example, Sanpellegrino have *models:* Day 15, Day 20, Day 40, Support 30, Support 50, Support 70, etc. By analogy, Glamour has alternative products: Edera 15, Eco 20, Ginestra 40, Positive Press 30, 50, 70, etc.

[12] Glamour's Edera 15 occupied ***32 positions****, as combinations of eight colors and four sizes:* fume 5, cappuccino 5, nero 4, cappuccino 4, fume 4, fume 3, cappuccino 3, castoro 3, glace 3, visone 4, miele 3, fume 2, castoro 2, cappuccino 2, visone 3, visone 2, bronzo 3, miele 2, bronzo 2, nero 2, nero 5, bronzo 5, etc. This list shows another problem – these positions were not sorted in proper order, because it was not done the first time they were entered into computer and allocated their code.

- *track actual demand,* that may be greater than actual sales if a stockout occurs, when all unfulfilled requests of the buyers ought to be noted or some other way found to attempt its reasonable estimate, so that *it includes all potential sales,* but only *at the regular price;* and
- *therefore exclude discounted sales from actual demand,* using different classification in the new Nomenclature of items for the items sold at a regular and at a discounted price; as well as
- *keep* permanent *record of past forecasts and forecast errors analyses,* in order to choose the most adequate standard deviation of demand in the future.

3. STATEMENT OF THE PROBLEM & PRIMARY DATA COLLECTION AND PROCESSING

In order to provide classic tights in sufficient quantities and assortment under these circumstances, *two problems are to be solved. The first is demand forecast and the second is optimal order quantity.* So, if history really tends to repeat itself and if seasonality effects are present in tights sales, the question is *how we can forecast monthly classic-tights demand by sizes and thickness in reasonably accurate and reliable way.* Even if we can predict the volume and structure of our future demand, we still wonder *what are the expected-profit maximizing quantities of classic tights by thickness to order each month.*

With *no secondary data* directly related and applicable to this research, the first step was to *collect* all relevant *primary data.* The problem with above-mentioned accounting computer program was the imposibility to get directly data as needed, but only in the form of *reports with past sales data for all months and years of the observed period by the producer, and not by thickness nor by size. So we had to classify, calculate manually, and consolidate raw data by thickness categories and by sizes,* which was a time-consuming procedure, but experience with gathering data was useful. *New nomenclature* with codes for each item *will be systematical,* and each digit in the code will bear specific information of: manufacturer, type of hosiery, thickness, model, color, and size. The new *accounting computer program* should be able *to produce reports not only by* manufacturers, but by any of these parameters.

Having finally organized primary data in two chronological tables by sizes and thickness categories, we systematized them all in a matrix, summary table.[13] With so large sample as ours, representative data[14] and a time series twice as long enough, with 60 observations, parametric statistical procedure implied the use of mean as a measure of central tendency, and standard deviation as a measure of dispersion about the mean, useful to describe “average” deviation. Therefore, to make data easier to manipulate, we sorted them by months, and to determine relative proportions in total monhly volumes of sales, as the approximation of actual demand, we transformed absolute amounts into percentage shares. The actual sales data for five years were used as the basis of the forecast for the following year.

4. SALES / DEMAND FORECASTING MODELS

Keeping track of a number of *time series* (like figures on sales and inventory) is needed to *forecast* future values *of* such *quantitative variables.* Estimation of their expected levels is needed in preparing business plans. If some kind of systematic variation in the past behavior of the time series variable (such as predictable seasonal pattern in the actual data values) is discovered, an *extrapolation model* (that can produce - as much as possible - accurate forecasts of its future behavior and predicted values) should be constructed or chosen among available models. Given the complexity of forecasting, instead of constructing a completely new model, we used Oracle’s computer program *CB Predictor™.*

[13] A limited space for this article does not allow us to present these data nor project results either in form of tables nor graphs.

[14] Although the research was based only on one importer’s sales data, we find them *representative enough* because: about two thirds of all retailers in the branch purchased from this importer regularly or from time to time; those retailers are located practically in all towns and areas of Serbia; their dispersion is approximately in direct proportion with the population density of those regions; and they comprise various types and sizes of retail stores, situated at different types of location.

It is an easy-to-use, graphically oriented, forecasting Excel add-in and extremely useful addition to the *Crystal Ball®, Professional Edition* suite of products. It analyzes past trends and patterns in the time-series data collected over a time period in order to predict possible outcomes in a relatively stable situation.

In order to examine a set of values ordered in equally spaced time intervals and project likely results, *time-series* forecasting breaks down *historical data* into *four components:*

- *level,* being a forecast starting point, expressed by parameter *alpha* ($0 < \alpha < 1$),
- *trend* of a consistent, long-term rise or fall, with parameter *beta* ($0 < \beta < 1$),
- *seasonality,* represented by data cycles and parameter *gamma* ($0 < \gamma < 1$), and
- *error,* as the difference between the actual and the predicted data values.

According to the presence of trend and seasonality components (and thus possible or not application of smoothing method parameters β and γ), *time series and methods (or models) applied by the above mentioned CB Predictor™ for their forecasting* can be classified as in the following table.

Table 1 Classification of Time-Series Forecasting Methods

METHODS		**STATIONARY**	**NONSTATIONARY**
	For volatile data …	***… with no trend***	***… with a trend***
NONSEASONAL	***… with no Seasonality***	**Single Moving Average**	**Double Moving Average**
		Single Exponential Smoothing	Holt's **Double Exponential Smoothing**
SEASONAL	***… with Seasonality***	**Seasonal Additive**	**Holt-Winter's Additive**
		Seasonal Multiplicative	**Holt-Winter's Multiplicative**

While non-seasonal methods estimate a trend by removing extremes and reducing data randomness, resulting in *straight* flat- (for 'single') or sloped-*line* forecasts (for 'double'), seasonal models combine smoothing data with an adjustment for seasonal behavior, resulting in a *curved forecast reproducing* the *seasonal effects: additive* have a steady pattern amplitude *and multiplicative* have a pattern amplitude changing over time. Seasonal *Additive / Multiplicative* smoothing methods calculate a seasonal index for historical data not having a trend but with seasonality that *doesn't change / increases or decreases* over time. It is *added to / multiplied by* the exponentially smoothed forecasted values, as it can be seen in the following equations, in which the *parameters* (beside $\boldsymbol{\alpha}$ - alpha, $\boldsymbol{\beta}$ - beta, and $\boldsymbol{\gamma}$ - gamma) are:

m - the number of periods ahead to forecast, **s** - the length of the seasonality, $\mathbf{L_t}$ - the level of the series at time t, $\mathbf{b_t}$ - the trend of the series at time t, and $\mathbf{S_t}$ - the seasonal component at time t.

/1/ (Level) $\mathbf{L_t = \alpha * (Y_t - S_{t-s}) + (1 - \alpha) * L_{t-1}}$

/2/ (Seasonal) $\mathbf{S_t = \gamma * (Y_t - L_t) + (1 - \gamma) * S_{t-s}}$

/3/ (Forecast for period m) $\mathbf{F_{t+m} = L_t + S_{t+m-s}}$

/4/ (Level) $\mathbf{L_t = \alpha * (Y_t / S_{t-s}) + (1 - \alpha) * L_{t-1}}$

/5/ (Seasonal) $\mathbf{S_t = \gamma * (Y_t / L_t) + (1 - \gamma) * S_{t-s}}$

/6/ (Forecast for period m) $\mathbf{F_{t+m} = L_t * S_{t+m-s}}$

Holt-Winters' ***Additive / Multiplicative*** seasonal methods are an extension of Holt's exponential smoothing, based upon equations BELOW. For data with trend and seasonality that *doesn't intensify / becomes more pronounced* over time, they *add / multiply* the seasonality factor *to / by* the exponentially smoothed values for level, (upward or downward) trend, and seasonal adjustment to the forecast. To find the initial values, ***Holt-Winters' additive*** seasonal smoothing model calculates:

/7/ $$\mathbf{P = \left(\sum_{t=1}^{s} Y_t \right) / s}$$ and sets:

$$/8/ \qquad L_t = P\,,\; b_t = 0\,,\; S_t = Y_t - P\,,\; \text{for } t = 1 \text{ to } s.$$

For the remaining periods, this model uses the following formulas:

$$/9/ \quad \text{(Level)} \qquad L_t = \alpha * (Y_t - S_{t-s}) + (1 - \alpha) * (L_{t-1} + b_{t-1})$$

$$/10/ \quad \text{(Trend)} \qquad b_t = \beta * (L_t - L_{t-1}) + (1 - \beta) * b_{t-1}$$

$$/11/ \quad \text{(Seasonal)} \qquad S_t = \gamma * (Y_t - L_t) + (1 - \gamma) * S_{t-s}$$

$$/12/ \quad \text{(Forecast for period m)} \qquad F_{t+m} = L_t + m * b_t + S_{t+m-s}$$

To find the initial values, ***Holt-Winters' multiplicative*** seasonal model calculates:

$$/13/ \qquad P = \left(\sum_{t=1}^{s} Y_t\right) / s \qquad \text{and sets:}$$

$$/14/ \qquad L_t = P\,,\; b_t = 0\,,\; S_t = Y_t / P\,,\; \text{for } t = 1 \text{ to } s.$$

For the remaining periods, this model uses the following formulas:

$$/15/ \quad \text{(Level)} \qquad L_t = \alpha * (Y_t / S_{t-s}) + (1 - \alpha) * (L_{t-1} + b_{t-1})$$

$$/16/ \quad \text{(Trend)} \qquad b_t = \beta * (L_t - L_{t-1}) + (1 - \beta) * b_{t-1}$$

$$/17/ \quad \text{(Seasonal)} \qquad S_t = \gamma * (Y_t / L_t) + (1 - \gamma) * S_{t-s}$$

$$/18/ \quad \text{(Forecast for period m)} \qquad F_{t+m} = (L_t + m * b_t) * S_{t+m-s}$$

Having identified an isolated pattern's level, trend, and seasonality, we can statistically *measure* the remaining random *error* (not explained by the forecast formula or by the trend and seasonal patterns) *to estimate how well the pattern explains the past behavior* of the time series variable, reproducing historical data, *and how accurately it projects* them into *the future.* It can be done by constructing line graphs showing the actual data plotted versus the values fitted and predicted by the best model, or by using quantitative error measures of the "goodness of fit" to compare the quality of different forecasts. *To compare* the quality of the results of different time-series forecasting *methods,* we should *check* all three *errors:* RMSE - root mean squared error, MAD - mean absolute deviation, and MAPE - mean absolute percentage error. When determining the best method, CB Predictor™ calculates selected error measure when fitting each method to the historical data. It tries all of selected forecasting methods from the Methods Gallery and then *ranks them according to which method has the lowest error. The method with the lowest error measure is considered best,* and the rest of the methods are ranked accordingly. By default, CB Predictor™ uses the RMSE statistic to determine which method is best.

5. SIMPLE NEWSVENDOR MODEL USED TO ESTIMATE OPTIMAL ORDER QUANTITY

Although we may have a most accurate, *sophisticated* forecast of future stochastic demand, we can never predict it for sure. *As we need sufficient quantities and satisfactory assortment on inventory,* our task is to *match supply and demand,* even though supply has to be provided before observing demand, which is (to be more amusing) - uncertain. It means that two weeks before the beginning of the next month and *between two and six weeks before* our random *demand occurs, we must take a firm bet regarding how much inventory to order.* A month and a half later, unless we are very lucky, we will learn that we have ordered either too much (because demand was less than our order) or too little (because demand exceeded our order). *To capture* this *trade-off between ordering too much and too little, and to determine the optimal quantities to order* (so that we can maximize our expected profit), we applied *newsvendor model,* showing that even such simple models can be very useful in business. To *implement it,* beside demand forecast, we ought to identify our procurement costs and selling prices as well as how much uncertainty in the demand we may expect, or an estimation of our forecast error.

Maximizing expected profit imposes minimizing costs for ordering too much and ordering too little. The first, per-unit *overage cost* C_o (of *over* ordering) means the loss that incurres whenever we order a pair of tights which is not sold within a month upon its arrival in the warehouse. It is the cost of capital that could have otherwise been invested in some similar project, converted into securities, or put in the bank, or – not borrowed. The second, per-unit opportunity or *underage cost* C_u (of *under* ordering) is the gain lost if we have not ordered a pair of tights that could have been sold in the coming month. It is equal to gross margin per that unit of sales. We calculated first weighted average per-unit acquisition or import cost of goods sold, including all per-unit costs as well as customs duty to be paid franco our warehouse, that depend on the number of units ordered, while excluding our labor force and all other variable and fixed selling and administrative costs not to be affected by our order quantity decision.

Then we calculated weighted average per-unit wholesale price, also without V.A.T., and using again as weights the relative shares of different models of tights in the previous year sales per each thickness category. Dividing their difference (absolute amount of unit gross margin) by average unit wholesale price, we obtain Cu or *relative unit gross margin.*For ordered quantity of *Q* units, the probability we shall not sell an additional *(Q^{th})* pair of tights increases, rising the *expected loss* from that marginal unit, as the product of the overage cost and the probability it is left in inventory,is: $\boldsymbol{C_o \times F(Q)}$, while the probability that we shall sell that pair decreases, reducing the *expected gain* from it, as the product of the underage cost and the probability that pair of tights is sold, which is equal to $1 - F(Q)$, so the expected gain will be: $\boldsymbol{C_u \times [\, 1 - F(Q)\,]}$. Since we should continue ordering additional units until the expected loss equals the expected gain, the *profit maximizing order quantity* is the order quantity *Q* that sets the expected loss on the Q^{th} marginal pair of tights equal to the expected gain on it.

Or: $\boldsymbol{C_o \times F(Q) = C_u \times [\, 1 - F(Q)\,]}$. From this we can get the expected profit maximizing order quantity *Q* such that demand is equal to or less than *Q* with probability that corresponds to the *critical ratio,* as the quotient of underage cost and the sum of both underage and overage costs: $\boldsymbol{F(Q)= C_u / (C_u+ C_o)}$. Since overage cost is given in percentages per month, we shall use gross margin per pair of tights in percentages, too, that differ *for each thickness category.* The above equation explains why our demand forecast has to be distribution function. CB Predictor™ has automatically calculated the statistics (mean and standard deviation) for five-year historical sales data series by tights thickness, showing our demand forecast is Normal distribution. We find the value of *z-statistic* (or optimal order quantity if our demand forecast is the Standard Normal), such that: $\boldsymbol{\Phi(z) = C_u / (C_u + C_o)}$. To convert it into *expected-profit maximizing order quantities Q for the actual Normal distribution* for the whole year*,* we shall apply the equation: $\mathbf{Q = \mu + \sigma \times z}$**,** where mean $\boldsymbol{\mu}$ of the Normal distribution are our demand forecasts for each thickness series and month in the year to forecast, while historical standard deviations $\boldsymbol{\sigma}$ per thickness series and month as well as z-statistica are from the tables we calculated. The *underage cost for all thickness categories is greater than* the *overage cost,* and the critical ratio is thus greater than 0.5, ranging from 0.837 for 20 den to even higher values for all other categories.

6. CONCLUSION

Due to the *seasonal pattern* present in historical sales data, taken as approximation of actual demand data, only seasonal time-series forecasting models were tested by CB Predictor™ and *Holt-Winter's Multiplicative* smoothing *method,* incorporating a (downward) trend component, proved to be the best method for all four sizes and the majority (five out of eight) of thickness categories. According to error measures, the remaining three thickness categories were more accurately and reliably enough predicted by stationary models, not accounting for trend: Seasonal Additive and Seasonal Multiplicative model.

To determine optimal order quantities by thickness categories for future monthly orders, maximizing the expected profit was selected as the main business objective. Therefore, *the newsvendor model* was applied, *balancing the overage* costs for ordering too much *and underage costs* for ordering too little. Due to the high critical ratio and because it is more expensive to lose a sale of any pair of tights than to have it in left-over inventory, *the expected-profit maximizing order quantities* tend to be larger than expected demand. We should not blindly order monthly quantities based on these results. They have to be *reduced by the inventory currently available,* so that we shall not have too much inventory, and at the same time, we will probably have always enough merchandise to satisfy the future demand. The optimal quantities grouped by thickness categories we obtained by the newsvendor model in practice have to be *divided further into sizes* (of course, based on our demand forecast by sizes) *and colors*.

We belive both models and the results of this project can be used by other companies in the branch, as well as by other importers and wholesalers dealing with goods having similar seasonal characteristics.