A Novel Method Based on Artificial Neural Network to Production Planning: a case study of a paints producer

Gionata Carmignani [1], Mauro Passacantando [2], Giuseppe Tumminelli [1]

[1] Dept. of Energy, Systems, Territory and Construction Engineering, University of Pisa
Largo L. Lazzarino, 2 – 56122 Pisa, Italy
gionata.carmignani@ing.unipi.it
tumminelli.g@gmail.com

[2] Dept. of Computer Science, University of Pisa
Largo B. Pontecorvo 3 - 56127 Pisa, Italy
mpassacantando@di.unipi.it

Abstract

Production planning is a challenging problem in the field of management science. It involves a wide set of decisions to be taken on different time ranges (long term, medium term or short term) which depends on the specific manufacturing system. Traditional mathematical models have been shown to be too restrictive in real situations characterized by uncertain and non-stationary demand. The paper shows that the Artificial Neural Network (ANN) systems are suitable for solving production planning problems thanks to their capability to adapt to the context. The literature contributions on ANN-based planning are usually applied to very specific aspects of the production planning, often involving assumptions which makes the model different from reality. The systems proposed in this paper involve instead the whole planning activity on medium-long term horizon and take into account essential features that are usually ignored, such as the importance of a product for the business strategy. In particular, two ANN-based systems are proposed, a static structure and a dynamic one, which are applied to a real production planning case: a paints and varnishes producer with a make-to-stock production system based on batch production mode. The developed ANNs provide good results in planning the activity on medium and long time horizons. Furthermore, the paper proves that the limited availability of data can be successfully faced by acting on the input parameters, on the one hand, and by developing appropriate scenarios on the other one.

Keywords: production planning problems, artificial neural networks, applied case study, static and dynamic structure

1. Introduction

Nowadays all firms must deal with a strongly complicated and competitive environment which is continuously changing. This is a very fast market and an increasing number of firms is not able to follow its dynamics. Moreover, the market system is dominated by a strong uncertainty which brings demand and offer trends to be very unpredictable. In a similar situation, the companies need a more rational and organized management of the whole business system; this can be achieved through a structured and accurate programming activity (the planning activity). The production planning process aims to harmonize the market demand, expressed by a demand forecasting and by an order book, with the target budget and the potential of the production system. This must be obtained by complying (i) with the market constraints expressed by the size of the required mix, by the pace of demand and delivery terms or (ii) with the offer constraints expressed by the saturation of machinery, by the investment limitations on warehousing and by the specific supply relationships, paying attention to the environmental and security issues. In general, the production planning is a decision-making process that relies on mathematical techniques and heuristic methods to allocate limited resources (machines, labour, facilities, etc…) to the necessary activities. This allocation of resources has to be done in such a way that the company optimizes its objectives and achieves its goals (Pinedo, 2009). The main goal of the planning function is to get the estimated quantity of the desired product, within the desired time to market, in the desired place and at the minimum global cost. Several authors have proposed mathematical programming models in order to develop optimal aggregated plans from an economic standpoint (Pinedo, 2009), (Caramia and Dell'Olmo, 2006), (Mula et al., 2006). In particular, some models dedicated to the cost minimization in production lines (Bowman, 1956) or to the resource cost minimization in short period planning (Hansmann and Hess, 1960) have been proposed. Other models have been developed in order to solve lot-sizing and scheduling problems (Manne, 1985), (Dzielinski and Gomory, 1965), (Lasbon and Terjung, 1971), (Eppen and R.K., 1987), (Karmarkar et al., 1987). Rajagopalan and Swaminathan (2001) proposed a model with the aim to coordinate production planning with changes in production capacity and inventory management; whereas, other models are focused on production management under the uncertainty resulting from the unpredictability of trends in demand or exchange rate (Kazaz et al., 2005). The lot sizing problems have been shown to be hard to solve if there is more than one level of production, more than one item to be produced or there are constrained resources (Bitran and Yanasse, 1982), (Florian et al., 1980). Moreover, in real life cases the complexity of these models is increased by the typical and strong uncertainty of the production environments (Mula et al., 2006). This uncertainty can be due to unexpected variations on demand, prices or resources constraints, inventory targets, inventory record errors or scrap losses. The mathematical formulation of a production planning problem can be very complicated: the model should face the possibility of systematic demand forecast errors and the desired inventory levels and it should include a timeline view extended on the basis of the product type and the knowledge of available production capacity. Complexity of the scope, uncertainty about the variables, time horizon, the need to include a large number of variables, the risk evaluation and risk-taking represent the real limit of the mathematical models (Mula et al., 2006). Moreover, even when it is possible to establish a correct model for a production planning problem, this is usually very complicated to solve. The choice of the solving algorithm plays a key role, not only in terms of processing costs, but also in terms of choosing an optimal solution (Florian et al., 1980).

The purpose of this paper is to propose new methods based on Artificial Neural Networks (ANNs) for solving production planning problems in a dynamic, effective and efficient approach. This approach can be beneficial because the ANN systems are able to:

1. Solve combinatorial optimization problems (Smith, 1999), which are often associated with the optimization of production scheduling;
2. Solve nonlinear optimization problems, which are often used to formulate production planning problems (Florian, et al., 1980);
3. Solve problems in a dynamic way considering rolling horizons;
4. Solve a problem without the knowledge of the underlying mathematical model;
5. Generalize: assuming a re-training of the network, it is possible to solve different problems using the same network.

In the literature there are few ANN-based contributions to solve production planning problems and they are often applied only to some specific aspects of the planning activity. Ntuen (1991) used ANNs to map production elements such as the lead-time, time between orders, the service rate; Gaafar and Choueiki (2000) applied neural networks to MRP problem of lot sizing; other contributions show the application of ANNs to the lot-sizing problems considering the costs of the stock and the stock reorder (Haizan et al., 2006), (Zwietering et al., 1991). In other cases, the neural networks were applied to specific industries, e.g. the automotive (Sharma and Sinha, 2012). Wilhelm et al. (2012) proposed the use of aggregate neural systems and expert systems for production planning. Rohde (2004) applied ANNs to the planning objectives for short-term plans for a single-stage production line.

The main limitations of the mentioned contributions are due to the very specific aspects of the production planning to which the neural models have been applied. This is often done by making a priori assumptions which distance the model from reality and undermine an effective application. Moreover, some of the models mentioned above do not take into account some important variables for the planning decisions (e.g. the importance of a product for the business) and do not consider situations where the production capacity is drastically reduced and varies significantly over time. These models do not consider the trade-offs resulting from a planning activity which involves a whole production department (usually they consider a single product). Furthermore, they consider the demand as perfectly known and they do not attempt to solve the trade-off generated by targets on Service rate and on Inventory-level. Finally, these models do not try to balance the production during the year, hence they usually generate some production peaks followed by periods with no production.

From a theoretical point of view, in some cases, the potential of neural models is not fully exploited. The network structures are often already assigned and no comparison is developed between significantly different ANNs. Many of these models are limited by the use of multilayer perceptron models and they do not take advantages by using time-based ANNs.

In this work we propose two ANN models in order to overcome the limitations of the mentioned above approaches. The proposed models have been applied to an entire production department, they consider constraints on production capacity (often very stringent) that vary over time, the importance of each product for the company turnover and possible errors in forecasting demand. Furthermore, they are capable to balance the production throughout the considered period. The effectiveness of the models is attested by an application to a real case: the production planning in a varnishing company.

The paper is organized as follows. In Section 2 a general illustration of the ANN systems and a deep explanation of the adopted methodology are shown. Section 3 is devoted to the case study description and the application of the proposed ANN models. The final section reports the numerical results of the applied models and a comparison between them.

2. Research Methodology

Neural Networks (Haykin, 2005) are an information processing system inspired by the dynamics of the biological nervous systems. Such systems are constituted by a dense network of simple units, called neurons, connected between them. Some of these neurons receive information from the external (input neurons), others provide information to the external network (output neurons), others exchange information between each other within the network (hidden neurons). Each unit is activated if the amount of signal received is higher than a certain threshold. In this case the unit revises the information and transmits a signal to the units directly connected to it. The input-output function, namely the transfer function of the network, is obtained through a learning process based on empirical data. In the considered cases two learning algorithms, belonging to the supervised learning family, have been used. These methods are based on the preparation of a set of inputs and desired outputs of the system (training set), in order to allow the network to identify the relation between the inputs and the outputs. Two ANN models have been analysed: the Feed-Forward Neural Network (FFNN) and the Nonlinear Autoregressive Network with Exogenous inputs (NARX).

Feed-Forward Neural Network (FFNN): a feed-forward neural network is an artificial neural network where the connections between the units do not form a directed cycle (Fig. 1).

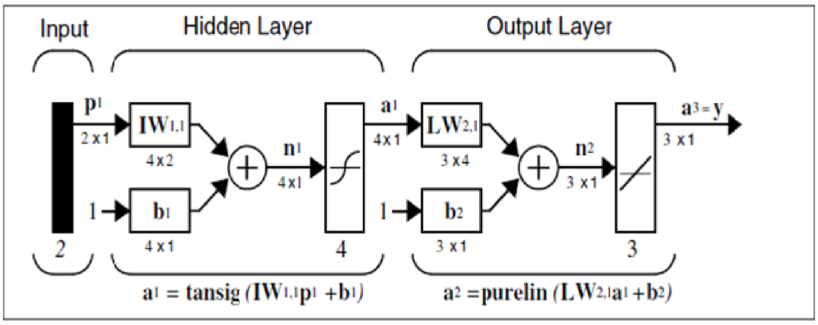


Figure 1: Model of a Feed-Forward Neural Network

This structure has often one or more hidden layers of nonlinear neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors.

Nonlinear Autoregressive Network with Exogenous inputs (NARX): a NARX Network is a recurrent dynamic network, with feedback connections enclosing several layers of the network. The NARX model is based on the linear ARX model, which is commonly used in time-series modelling. The defining equation for the NARX model is:

$$y(t) = f\left(y(t-1), y(t-2), \dots, y(t-n_y), u(t-1), u(t-2), \dots, u(t-n_u)\right)$$

where the next value of the dependent output signal *y(t)*is regressed on the previous values of the output signal and the previous values of an independent (exogenous) input signal. Fig. 2 shows a general scheme of a NARX Network.

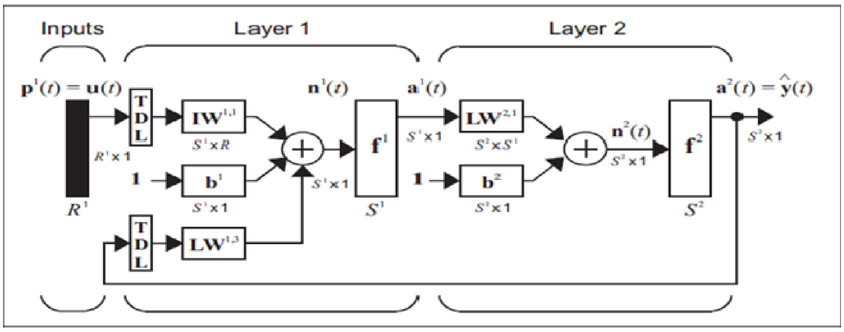


Figure 2: Model of Non Linear Autoregressive Network with exogenous inputs (NARX)

The learning algorithms used for the two systems are the Levenberg-Marquardt Algorithm (for the FFNN model) and the so-called "Bayesian Regulation Back-propagation" (for the NARX model). The Levenberg-Marquardt algorithm, blending the steepest descent method and the Gauss-Newton algorithm, allows to overcome the problems encountered in the application of these methods to the ANNs. It inherits the speed advantage of the Gauss–Newton algorithm and the stability of the steepest descent method. It is considered one of the most efficient training algorithms for feed-forward networks (Hagan&Menhaj, 1994). The Bayesian Regulation Back-propagation is a network training function that updates the weight and the bias values according to Levenberg-Marquardt optimization. It minimizes a combination of squared errors and weights and determines the correct combination in order to produce a network that generalizes well (MacKay, 1992). The choice of these two models allows to consider and compare the contribution to the planning activity generated by a static neural structure (that is able to highlight the causal relationships between input and output), and a dynamic neural structure which includes the time variable. Both approaches should develop a production plan that includes all typical constraints of this activity and tries to overcome the limitations of the current mathematical models (see Introduction). The research methodology involves the steps reported in Fig. 3.

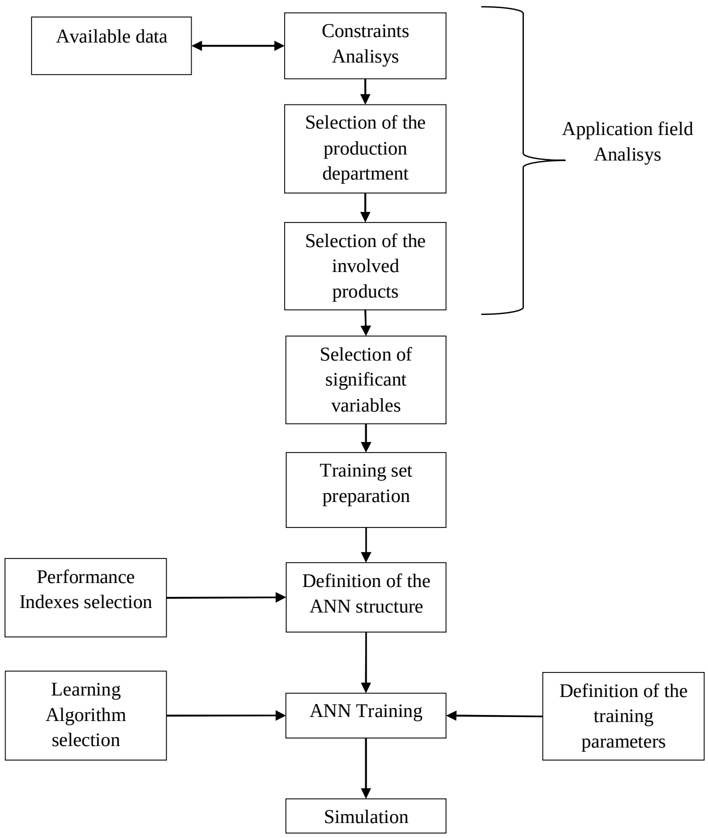


Figure 3: Methodology workflow

3. Case study

The effectiveness of the proposed models is proved by the application to a real case, which provided positive results. The case is related to a paints and varnishes producer, sited in Italy, operating in the European and world market. It is a make-to-stock production system with batch production mode.

3.1 *Production process and planning constraints*

The reported case is related to the middle term planning activity. This phase starts from the Master Production Schedule (MPS) and determines what to produce, when to produce and in which quantities, with a high degree of detail. In practice, during this phase, the MPS is split into months and weeks, with an usual time horizon of three months and considering the production of each item. This planning phase must try to respect the capacity constraints and face the "Service Level/Inventory costs" trade-off in the short term. Specifically, the production lot is constituted by a certain fixed quantity of liquid (the coating product) which is then packaged in a number of cans differing for size and type. The demand trend of the products is very different each other. Therefore, the production of a batch of liquid may not be efficient if it is required to meet the demand of only one of the finished products, especially if this product shows low sales on average. The planning activity is exposed to several technical constraints: the size of the production batches is fixed, the method of packaging with different patterns of demand for each products, the production capacity varies over time. These factors force the planner into complicated decisions oriented to face the multiple trade-off "demand satisfaction / cost of inventory / production costs / optimization of capacity utilization". In this case the problem of lot-sizing becomes a problem of lot-quantity, hence it is necessary to decide how many liquid batches have to be produced in each period and how to package the quantities produced from time to time. Three types of liquid have been selected between those that are made on the "Water Dissipater Plant": Transparent Base (1000 kg batch), Opaque White (9000 kg batch), White satin (1000 kg batch). These three liquids can be packaged in several cans differing by type and size obtaining 29 final products. The production capacity of the plant is defined as the number of batches produced per week. This value was calculated as the average number of batches produced in the last 4 years.

3.2 Feed Forward Neural Network (FFNN) Model

<u>Selection of significant variables</u>

It is very important to select the most relevant variables for the model as well as to choose the correct number of involved variables. A large number of variables allows a better description of the model, but it will be more expensive in terms of processing and requires a very large training set; on the contrary, a low number of variables could invalidate the results, some key variables may be not considered by the system and it could lead to a wrong plan.

For the case study the following variables have been chosen: period of the year (the week), ABC classification (the importance of each product for the turnover), weekly sales forecast, stock level for each product, weekly production capacity, standard batch size.

Since there are 29 products, the input vector is composed by 92 variables. It is clear that, a so large input vector would lead to the creation of a big neural network as well as to the preparation of a huge training set. In order to reduce the number of input variables, still maintaining the information provided by the chosen ones, it has been used the so-called "Coverage Ratio". This quantity can be calculated as follows:

$$RC_i(t) = \frac{C_i(t)}{Cd_i}$$

where $RC_i(t)$ is the "Coverage Ratio" for the product i at the period t, $C_i(t)$is the actual coverage of the product i at the period t (that is, the time interval such that the stock level satisfies the expected sales) and Cd_i is the desired coverage of the product i(that is, the required coverage on the basis of the product importance for the turnover).The actual coverage, that is the number of days (k) for which the inventory level (S) will cover the expected sales (B), can be expressed as follows:

$$C_i(t) = max\left\{k \mid \left[S_i(t) \geq \sum_{z=1}^{k} B_i(t+z)\right]\right\}$$

where $S_i(t)$ is the inventory level of the product i in the period t and $B_i(t)$ represents the expected sales of the product i in the period t. It is clear that the “Coverage Ratio” allows to include the following variables into an unique indicator:

- the ABC classification: the desired coverage Cd_i is closely linked to the ABC class of the product and therefore to the importance of the product for the company;
- the sales forecast: the actual coverage $C_i(t)$ includes the expected sales for the next periods (namely until the expected stock out);
- the inventory level: it is included in the actual coverage indicator.

The remaining variables (namely the batch size and the production capacity) are included in the training set. To summarize, the input variables are the week (t) and the “Coverage Ratio” ($RC_i(t)$of each product at the end of the week t). Hence, the input vector is composed by 30 elements ($RC_i(t)$*29 + t) instead of 92. The Fig. 4 shows the process of reduction of the involved input variables.

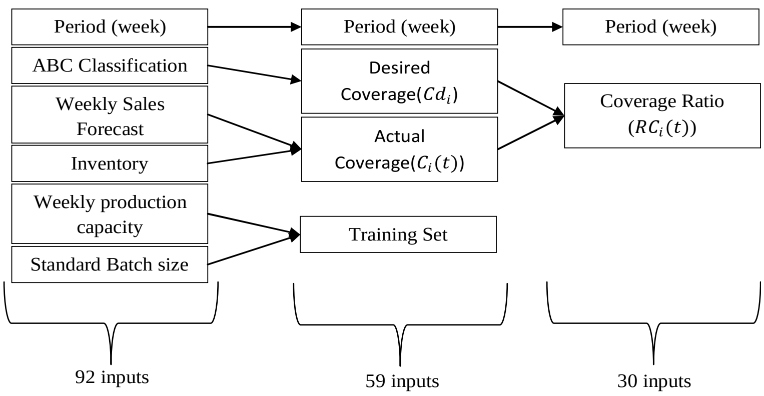


Figure 4: Reduction of input variables

<u>Training set preparation</u>

The training set is a set of input/output data pairs: input data are the Coverage Ratio ($RC_i(t)$) of each product and the period (t) or week, while output data are the number of batches P_i^t to be produced for each of the three liquids at each period t. These values has been calculated as an ideal plan based on actual sales (starting from a deterministic plan, depending on the coverage ratio values, the production was balanced during the year considering the production capacity).The examples in the training set has been arranged in order to meet the capacity constraints, this allows to incorporate the production capacity variable in the training set. The ANN systems require a large number of data for training. However, the available data for the case study are not enough for the purposes of an effective training and it has been necessary to generate the data in order to increase the size of the training set. Furthermore, the possibility to include the generated data increases the generalization capability of the network, because the ANN is less linked to the specific problem. The training set used in the numerical tests consists of 10,000 vectors generated as follows:

1. Calculation of the probability distribution of stocks for each period from 2008 to 2011;
2. Preparation of 200 samples of stocks for each period extracted from the probability distribution calculated in step 1;
3. Calculation of the Coverage Ratio $RC_i(t)$ of each item for each period and for each amount of stock;

4. Estimation of the quantity to be produced for each item in order to get the Coverage Ratio equal to 1 (based on actual sales);
5. Aggregation of the estimated quantities in order to decide the amount of liquid to be produced;
6. Rounding to the standard production batch;
7. Calculation of the number P_i^t of batches to be produced for each period.

In this way the training set includes also the systematic forecast errors. This is due to the fact that the simulation is based on sales forecast, whereas the network has been trained using actual sales data. Therefore, the network forecasts itself future sales taking into account the actual sales. The training set data have been normalized in order to obtain mean equal to zero and variance equal to one.

<u>Network structure</u>

In order to define the optimal network structure, the following iterative procedure has been used. First, a small size network is generated (three neurons and one hidden layer), trains the network, simulates the network using 2011 year data and calculates the performance (see equation (1)). The process is reiterated adding, each time, a neuron into the hidden layer. Once that the first layer of the network gets a certain size so that the performance does not improve significantly, the number of the first layer neurons is blocked and a second layer is added to the structure. The iterative process is repeated for networks with two hidden layers and the network with the best performance is selected.The selected network in the case study has been a FFNN with two hidden layers, 30 neurons in the input layer (the Coverage Ratio $RC_i(t)$ at time$t$ for each of the 29 involved items and the variable t referring to the period of the year), 18 neurons in the first hidden layer, 19 neurons in the second hidden layer, 3 neurons in the output layer, hyperbolic tangent transfer functions in the two hidden layers and a linear function in the output layer.

<u>Neural network training</u>

The training parameters have been set as follows: epochs=4000, performance goal=0.01, initial momentum=0.001, decrease momentum factor=0.1, increase momentum factor=10, maximum momentum value=10. The training set has been randomly divided in the following partitions: 80% training set, 10% validation set, 10% test set. The training performance has been valued by means of the following function:

$$msereg = \gamma mse + (1-\gamma) msw \qquad (1)$$

where γ is the performance coefficient, *mse* is the mean squared error and *msw* is the mean of the squared weights values, i.e.

$$msw = \frac{1}{n}\sum_{j=1}^{n} w_j^2$$

This function measures network performance as the weight sum of two factors: the mean squared error and the mean squared weight and bias values. Using this performance function, the network tends to get lower weights values: this allows to obtain smoother values as output and the output is less exposed to over-fit.

<u>Simulation</u>

In order to plan the weekly production for the year 2012, it is needed a system constituted by a series of 50 neural networks. The output of a network becomes the input of a function which determines how to pack the quantity of produced liquid basing on the sales forecast and recalculates the Coverage Ratios in the next period. This function is placed between each network and its consecutive one. Therefore, each network generates a "one step ahead" planning. The results of the simulation have been rounded to the closest integer number.

3.3 *Nonlinear Autoregressive Network with exogenous inputs Model (NARX)*

<u>Selection of significant variables</u>

The significant variables are the sales forecast $B_i(t)$ and the actual planning $y_i(t)$ (the weekly production volume during previous years for each item).

<u>Training set preparation</u>

The training set consists of real data (10%) and generated data (90%). Input data are sales forecast $B_i(t)$ for each period t, for the years 2010-2011; output data are the actual production volumes $y_i(t)$ for each period t, for the years 2010-2011. The initial state is constituted by the same data referring to the previous years: sales forecast $B_i(t)$ for each period t, for the years 2008-2009; actual production volumes $y_i(t)$ for each period t, for the years 2008-2009.The real data refer to the ideal production volumes realized in order to satisfy the demand and the production capacity during the previous years. These production volumes have been calculated starting from the actual inventory level at the beginning of the year. The generated data are based on the formulation of several "planning scenarios" elaborated as below:

1. Probability distribution calculation of the inventory level at the beginning of each year;
2. Elaboration of 100 possible inventory levels sampled from the probability distribution calculated at step 1;
3. For each of the 29 items and inventory levels, elaboration of the weekly ideal production volumes during the years 2009, 2010 and 2011.

The training set data have been normalized into the range [-1,1].

<u>Network structure</u>

The iterative procedure to define the network structure is the same as in the FFNN model. The selected network in the case study has been a NARX with two hidden layers, 58 input neurons (the sales forecast for the period t, $B_i(t)$, for each of the 29 involved items, and a delay block, for each of the 29 involved items, which collects the production volumes referring to the past periods $y_i(t)$), tapped delay line of 100 elements, 13 neurons in the first hidden layer, 16 neurons in the second hidden layer, 29 neurons in the output layer, hyperbolic tangent transfer functions in the two hidden layers and a linear function in the output layer.

<u>Neural network training</u>

The tapped delay line is constituted of a maximum of 100 elements, thus the network elaborates starting from the 101*st* element. Consequently, the tapped delay line must be charged with the first 100 values of the series and the inputs. The goal of the training is to plan the production volumes for the years 2010 and 2011. So the training set is structured as follows:

- Initial state: sales forecast $B_i(t)$ during the years 2008-2009 and production volumes $y_i(t)$ during the years 2008-2009;
- Input: sales forecast $B_i(t)$ during the years 2010-2011;
- Target: production volumes $y_i(t)$ during the years 2010-2011.

The training parameters have been set as follows: epochs=200, performance goal=0.01, marquardt parameter (momentum update) =0.005, decrease momentum factor=0.1, increase momentum factor=10, maximum momentum value=10.

<u>Simulation</u>

In order to elaborate the production volumes of the three liquids for the year 2012, it is needed to feed the network with the following elements. Initial state: sales forecast $B_i(t)$ during the years 2010-2011 and production volume $y_i(t)$ during the years 2010-2011. Input: sales forecast $B_i(t)$ for the year 2012.After the simulation, the outputs are mapped out of the range [-1,1] on the base of the minimum and maximum values for the year 2011. The production volume of each liquid is calculated aggregating the production volumes of the corresponding items. These volumes are rounded to the standard batch size or to the half of the standard batch size.

3.4 *Numerical results*

The simulation results have been compared with both the real planning activity during the year 2012 and a deterministic planning activity (performed considering an unlimited production capacity) based on the sales forecast. An example of the simulation results is reported in Table 1

week	Deterministic Planning			Real Planning 2012			FFNN Planning			NARX Planning			Production Capacity
	P1	P2	P3	P1	P2	P3	P1	P2	P3	P1	P2	P3	Number of Batches
18	1			1		1	1		1	1		1	2
19		0,5	0,5	1		1	1	1	1	0,5	0,5	1	2
20			1	1		1	1					1	2
21							1		1	1			2
22	1	1	1					1		1		1	2

Table 1: Production planning generated by the four approaches

Table 1 shows that the two proposed ANN models are capable to catch the underlying logic mechanism. Comparing the results obtained from the simulation with the real planning activity during 2012 and with the results of the deterministic planning, we notice that the ANN models generate a very plausible planning. The obtained production volumes respect the constraints dictated by the available weekly production capacity.

Table 2 compares the four mentioned models considering the monthly service rate (calculated as the ratio between the ordered and the fulfilled quantity using the available inventory) and the inventory level (average inventory amount for each period) generated by the simulations.

		Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.	AVE	RSI
Real. 2012	SL	0,86	0,91	0,97	1	0,89	1	0,9	0,94	0,91	0,85	0,87	0,91	**0,92**	**0,62**
	IL	801	1.262	1.301	1.460	1.198	1.316	1.828	1.999	1.978	1.810	1.680	1.120	**1.479**	
Det.	SL	0,9	1	1	0,98	0,97	1	0,93	1	0,96	1	0,98	1	**0,98**	**0,44**
	IL	1.010	2.011	1.860	1.720	1.990	2.010	2.024	2.089	3.089	3.097	3.199	2.770	**2.239**	
FFNN	SL	0,82	0,9	0,95	0,96	0,92	0,97	0,88	0,92	0,8	0,78	0,84	0,79	**0,88**	**0,53**
	IL	990	1.680	1.011	1.888	991	1.230	2.998	891	3.010	2.770	1.660	879	**1.667**	
NARX	SL	0,87	0,8	0,91	0,94	0,98	0,82	0,91	0,97	0,87	0,98	0,92	0,94	**0,91**	**0,69**
	IL	1.680	1.390	890	2.091	2.101	2.780	987	671	1.965	721	267	378	**1.327**	

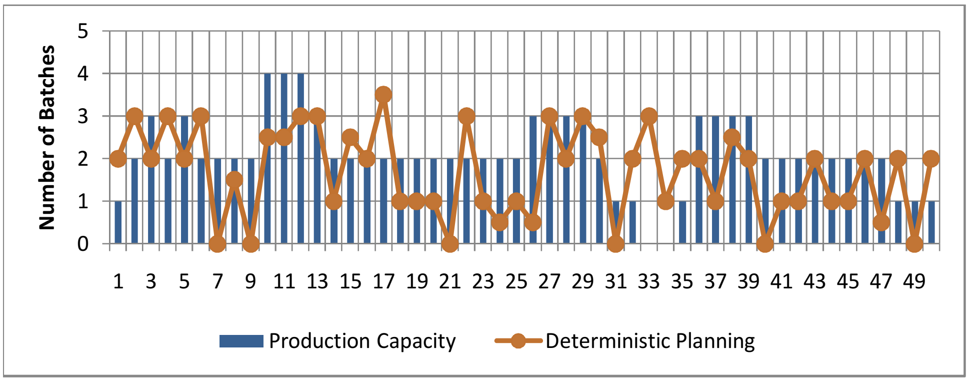
Table 2: Service Level (SL) and Inventory Level (IL) generated by the four approaches

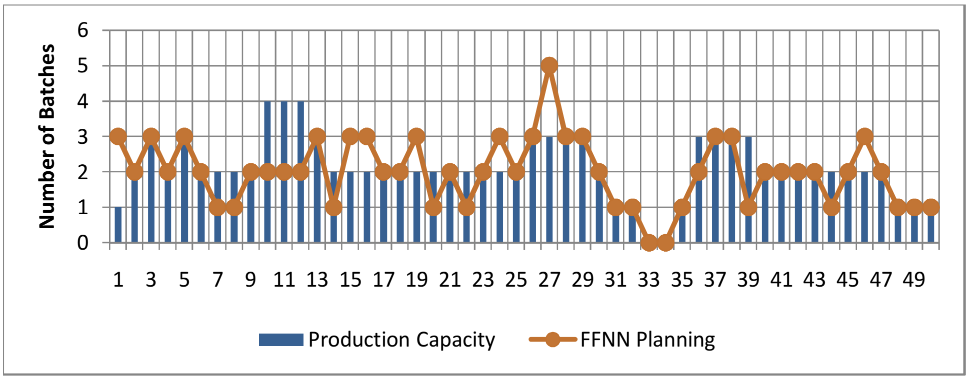
The NARX model generates a service rate during 2012 very close to the real planning activity (91% *vs.* 92%). This good outcome is probably due to the fact that the NARX network identified possible systematic forecast errors (elaborating an own internal forecast). The FFNN model generates a service rate of 88%, which is also a good result considering that the real planning is regularly updated (every 2 months), whereas the ANN models plan the production for the whole year only in a single elaboration (at the beginning of the year). The deterministic planning generates the highest service rate (98%), but it must be considered that it does not respect the production capacity constraints, so it generates a very high inventory level. The ratio between the service rate and the inventory level, called RSI, accords better results to the NARX model (0.69). The FFNN model (RSI = 0.53) generates an RSI better than the deterministic planning (RSI = 0.44), although still lower than the real planning RSI (0.62). Concerning the inventory level, the NARX model gives once again very good results: it generates, on average, an inventory level lower than the other models. Nevertheless, the trend during the year results unstable.Table 3 compares the models on the basis of 5 performance indicators connected to the production capacity exploitation: number of batches that exceed the weekly production capacity (total error), amount of weeks in which the production capacity is exceeded (number of mistakes), ratio between the number of errors and the total number of weeks in the observed period (% of saturation), ratio between the number of errors and the number of weeks in which the production capacity is totally employed (Ratio Errors/Saturations), ratio between the employed production capacity and the maximum available capacity (% of capacity exploitation).

	Real Planning 2012	Deterministic Planning	FFNN Planning	NARX Planning
Total Error	-	15,5	9	-5,5
Num. of mistakes	-	14	7	6
% Saturation	0,6	0,12	0,64	0,42
Ratio errors/saturations	-	2,33	0,22	0,29
% capacity exploitation	0,73	0,65	0,86	0,72

Table 3: performance indicators

Table 3 shows that the two ANN models have very good performance indicators with respect to both the real planning activity and the deterministic planning. Fig. 5 shows the exploitation of the weekly production capacity for each model. The two ANN models exploit the available production capacity in a more efficient way than the deterministic one, although they are still less effective than the real planning. Since the NARX model generates a percentage of exploitation lower than the FFNN one, it is clear that the first one is more flexible dealing with the demand peaks. However, this percentage of exploitation is really close to the real planning one. The NARX model chart shows a capacity exploitation trend that can be considered satisfactory. In particular, it correctly predicts the production volumes during the critical weeks (33rd, 34th, 35th in August) and those at the end of the year. Moreover, when the capacity is exceeded, the volumes can be anticipated/postponed without any effect both on capacity exploitation and service rate.





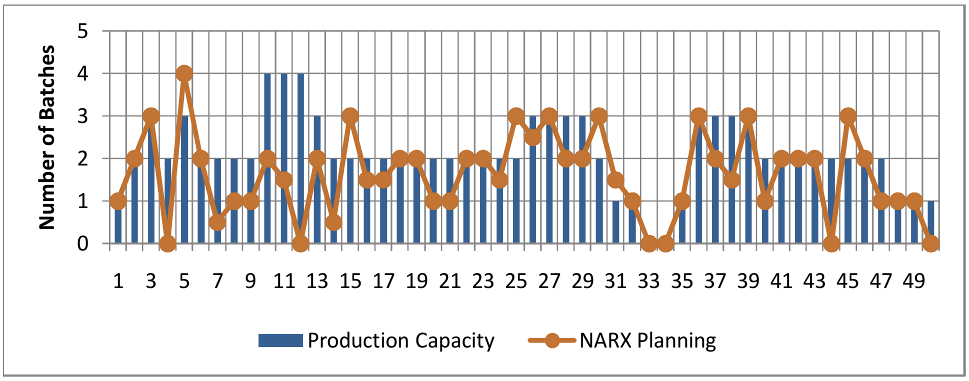


Figure 5: Available production capacity per week vs the required one by the used planning methods

4 Conclusions

The aim of this paper is to provide new support systems to the planning activity. These systems must be capable to overcome the main limitations of the traditional mathematical models and of the more recent ANN models. In order to achieve this aim, two new ANN planning models have been developed. These models allow to deal with: the constraints related to technical issues and to the time-varying production capacity, the importance of each item for the business, and the production smoothness policy.The first model employs a static network structure, so-called Feed-Forward, that does not include the time variable; the second model, the NARX one, employs a dynamic network structure, since it includes the time variable (delayed feedback connections in input). In order to validate the models it has been proposed an implementation to a real varnishing company. In particular, three liquids of the "Water Dissipater Plant" have been took in consideration. These liquids can be packaged as 29 different items. The goal is to plan the weekly production volumes for the whole 2012. The ANN simulations have been compared to a deterministic planning (with infinite productive capacity) and to the real planning elaborated in 2012. The case study outcomes shows that the aim has been reached: the ANN systems, both static (Feed-Forward) and dynamic (NARX), can be efficaciously employed as a support tool for the production planning activity.As for the next developments, it would be interesting to investigate an integration of the proposed planning tools into the enterprise data flow process. The planning tool could be fed by an ANN-based forecasting tool and a system providing real time information from the production department. Furthermore, the planning system could work on all production plants of the considered company in order to develop an aggregated MPS capable to balance the whole production capacity on the basis of the long term objectives.

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