Identification and Modelling of a Stock Level by Parametric Models

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Abstract*:*In this paper, we present a modelling of a warehouse inventory management system. Themodelling method used in this paper is an application of parametric identification with models(ARX, ARMAX, OE and Box Jenkins). The approach followed during this modelling is togenerate a mathematical model that faithfully represents the level of stocks in a warehouse from receptions and shipments.

Keywords* :*modelling, logistics system, inventory management, parametric identification, ARX, ARMAX, OE and Box Jenkins.

I. INTRODUCTION

The economic environment is constantly changing, leading to instability of demand and global competition that companies face. This change is mainly due to the reversal of the relationship between supply and demand, to the globalization of economic markets but also to technical and technological progress. Thus, the survival of companies depends on their ability to adapt to changes and their responsiveness that manifests itself in production and delivery on time at reduced costs by meeting high levels of service required by customers. Faced with the pressures of the environment, companies are required to master all the processes of the supply chain, However, the mastery and the optimization of the flows of the logistic systems very often require that one has a model capable of describe his dynamic behaviour. These models can be deduced directly from the physical laws that govern the dynamic behaviour of the system, but it is often impossible to obtain a complete and precise prior knowledge of all the parameters of the model. These parameters should therefore be identified to obtain a model that represents the "best" process. Precisely, since the parametric identification approach is a method often used in situations where it is not necessary to acquire a deep mathematical knowledge of the studied system, but it remains sufficient to predict its evolution over time, respecting the conditions of modelling. In our case, to refine and clarify this knowledge, we use behavioural models, intended to accurately represent the behaviour of a dynamic system from these inputs and outputs. The parametric identification approach consists in collecting the excitation data and the output of the dynamic system studied, processing its data to extract the parameters of a mathematical model, which will be used for the prediction and simulation of the dynamic system. However parametric identification is an approach widely used in different fields, and has been the subject of several scientific contributions. [AT. SUMALATHA & A. BHUJANGA] modelled a boiler drum level system from factory data using parametric model structures [13]. The presented model provides a dynamic model derived from real plant data that can be used effectively for control scheme design, allowing the design of more robust control structures. [E. Karadirek& al] The authors used ARX and ARMAX structures to predict KWDN critical point chlorine concentrations. The results obtained show that the ARX and ARMAX model structures can be considered as a potential for managing chlorine levels in water distribution networks, especially when the properties of the components and hydraulics of the distribution network of water are unknown [27]. B.Raafi'u&P.A.Darwito, presented a process of identification of the four-wheeled mobile robot system (FWMR). In this study, they studied the system as a single multi-entry system (MISO). The current and duty cycle of the input motors and the speed of rotation of the output wheel. The four-wheeled mobile robot model is constructed using parametric models (ARX and ARMAX) for system identification [28]. [H.SARIR& al.] Also presented a production chain model using discrete time behavioural identification by transfer functions, they used the PEM algorithm for model building and the simulation was carried out on the GUI (IDENT) in MATLAB© [6]. K.TAMANI& al. Proposed a product flow control process, in which they broke down the system under study as basic production modules. They then proposed control of the flow through each output module and supervision based on fuzzy logic [8]. [H. FOURAIJI & All] The authors have modelled a discrete flow dynamic production system, they used nonlinear parametric identification structures (NARX and Harmmerstein-Wiener). The best model found in this study is the NARX structure with a FIT = 95.57% [29]. K.Labadi& al. presented a modelling and performance analysis of logistic systems, based on a new model of stochastic Petri nets. This model is suitable for modelling flows in discrete quantities (many different sizes). It also allows for more specific activities such as sales orders, supply inventory, batch production and delivery [2].

Revised Manuscript Received on October 20, 2020.
Manuscript Received On October 06, 2020
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N. SMATA & al. presented a model of the global supply chain using variable speed Petri nets. They have transposed the concepts of traffic developed according to the type of supply chain (manufacturing). They also proposed a modular approach to model the different actors in the supply chain, always based on the formalism of variable speed Petri nets [3].

F.PETITJEAN& al. develop their work in a global modelling methodology of the supply chain from an audit of the company. Then, using the UML model, they realized a simulation platform and also proposed the principles of management of the integrated supply chain [4]. BROHEE & al. used hybrid Petri nets to provide an offline simulation approach that supports multiple constraints (change of control, time between developments, friction, etc.). The originality of their work lies in the fact that they proposed a simulation of the production of continuous pieces and the study of the interactions between the continuous model and the discrete data exchanged with the control part. This approach simulates and controls the system without using the actual operational part. These contributions are based on a schematic modelling, without considering the internal parameters of the studied system [5]. H.SARIR& al. presented an ongoing modelling and regulatory work approach to inventories in the macroscopic analogy of production lines with the hydraulic reservoir control model. They used automatic control concepts to monitor and control inventories during manufacturing [6].

Through this literature study we note that logistics systems are of great interest in the field of modelling and flow regulation [30].

On the other hand, we note that the modelling of the logistic systems by the parametric structures is rarely discussed, and most of the modelling methods used are (UML, Petri, Multi-agent ....).

For this purpose, we present in this paper an approach to modelling a stock management system by parametric identification, using model structures (ARX, ARMAX, OE and BJ).

II. IDENTIFICATION METHOD

System identification is a process for obtaining models based on a set of data collected from experiments. In a specific sense, the system identification consists of producing a precise model from the input-output signals recorded during the operation of the system under study. Historically, the identification of systems stems from the technical necessity of forming models of dynamic systems: so it is not surprising that the emphasis is traditionally placed on numerical questions, as well as on concerns related to systems theory [14]. In general, two approaches are frequently used to create mathematical models of dynamic systems: physical modelling and system identification. Physical modelling uses physical principles and laws such as Newton's second law of motion, Ohm's law or other laws to create mathematical models. Despite the good precision of the physical model obtained by this approach, it is not suitable for experimental modelling purposes because it is difficult to measure all the degrees of freedom of the system and the physical model is in continuous time whereas the measurements are obtained in discrete time. In addition, noise from unknown excitation sources and / or measurements must be taken into account in order to obtain a better representation of the vibrating structure. On the other hand, the system identification approach is used to develop mathematical models in the case of limited physical information on the dynamic system. Thus, this model can represent and reproduce the behaviour of the system on the basis of possible prior knowledge and by using the input / output data obtained [15].

Each process is determined by its elements and variables that cannot always be clearly defined. The modelling aims to highlight the essential aspects that constitute the dynamics of any process. Identification of an unknown system based on excitations (inputs) and its reaction (output). System identification is the process of identifying dynamic models of physical systems based on experimental or real-time data. This is an iterative process as shown in Figure 1 and includes the following steps.

- Understanding the basics of a system and acquiring prior knowledge.
- Design an appropriate experience that can reveal the most significant dynamics of the system.
- Gather an appropriate portion of the experimental data that can reflect the appropriate cause-and-effect relationship of the system under study.
- Choose the appropriate model structure.
- Select the appropriate criterion to analyse the fit of the model.
- Estimate the model.
- Validation of the model
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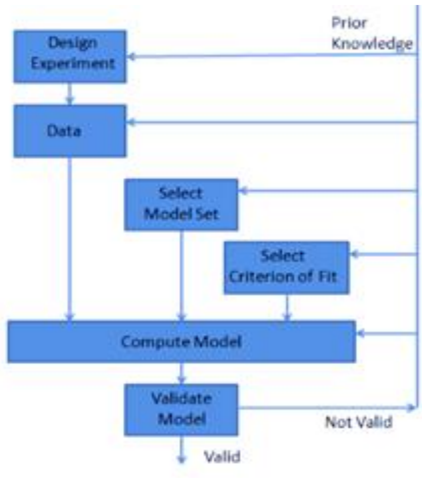

Figure 1 :Process of system Identification

In this work, we focus on the development of "black box" models of dynamic systems. We consider only the case of fixed systems, that is to say that the laws governing their behaviour do not change with time. The models we consider are discrete time models. Black box models are entirely data-based and do not require prior knowledge of the system. Data-based models describe the dependency of the output on the inputs. Other dynamic characteristics of the physical system, such as delay, response rate, time constant, etc., are not interpreted directly but by the analysis of results [4].

A. Acquisition of data

The first step in the identification process is data acquisition. This step is very important. Therefore, we must choose the data that will be used to model the system, since they must use data covering the entire telemetry system operating under normal conditions.

The input and output data must be divided into two sets of data, the first part of the data to be estimated and the second part of the data validation.

B. Choice of the model structure

The parametric model describes a system in terms of differential transfer function. There are few structural models that can be used to represent some systems. In general, the structure of the parametric model used is based on equation (1) [9].

$$y(t) = q^{-nk}G(q)u(t) + H(q)e(t)$$

With $q^{-nk}G(q)u(t)$ the output of the system without disturbance, $H(q)e(t)$ represents the disturbance of the system [1]. q is the argument of G(q) and H(q) this is the shift operator, which is equivalent to q^{-1} who is represented by q^{-nk} and can be demonstrated by $q^{-1}x(t) = x(t-1)$, nk is the delay in the sampling time between the input and the output of the process.

In the modelling process, always $nk \geq 1$ to ensure causality [2]. Four linear model structures are considered in this study (ARX, ARMAX, BJ and OE). In this paper, the studied system will be considered as a multi-entry system, a single output (MISO).

a) ARX model

The representation of the structure of the ARX model can be expressed as follows:

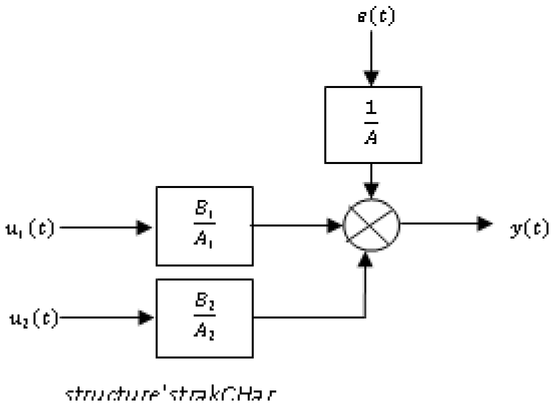

Figure 2 :The ARX model structure

We present this structure in the following compact form:

$$y(t) = q^{-nk}\frac{B(q)}{A(q)}u(t) + \frac{1}{A(q)}e(t) \quad (1)$$

Polynomials A(q) and B(q) are given by:

$$A(q) = 1 + a_1q^{-1} + \ldots + a_{na}q^{-na}$$
$$B(q) = b_0 + b_1q^{-1} + \ldots + b_{nb}q^{-nb}$$

$A(q)$ and $B(q)$ represent the parameters of the dynamic system, q^{-1} is the delay operator between the excitation and the response of the dynamic system, this description of is

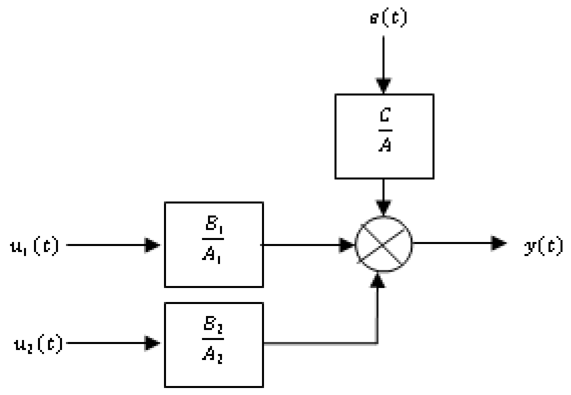

Figure 3 : the ARMAX model structure

equivalent to the transform in Z [10], $a_1 \ldots\ldots a_{na}$ and $b_1 \ldots\ldots b_{nb}$ its polynomials parameters $A(q)$ and $B(q)$.

b) ARMAX model

The representation of the structure of the ARMAX model can be expressed as follows:

We present this structure in the following compact form:

$$y(t) = q^{-nk}\frac{B(q)}{A(q)}u(t) + \frac{C(q)}{A(q)}e(t)$$

Polynomials A(q), B(q) and C(q) are given by:

$$A(q) = 1 + a_1q^{-1} + \ldots + a_{na}q^{-na}$$
$$B(q) = b_0 + b_1q^{-1} + \ldots + b_{nb}q^{-nb}$$
$$C(q) = 1 + c_1q^{-1} + \ldots + c_{nc}q^{-nc}$$

$A(q)$ and $B(q)$ represent the parameters of the dynamic system, C(q) represents the model of the disturbance, q^{-1} is the delay operator between the excitation and the response of the dynamic system, this description of is equivalent to the transform in Z [10], $a_1 \ldots\ldots a_{na}$, $b_1 \ldots\ldots b_{nb}$ and $c_1 \ldots\ldots c_{nc}$ its polynomials parameters $A(q)$, $B(q)$ and $C(q)$.

c) OE model

The representation of the structure of the OE model can be expressed as follows:

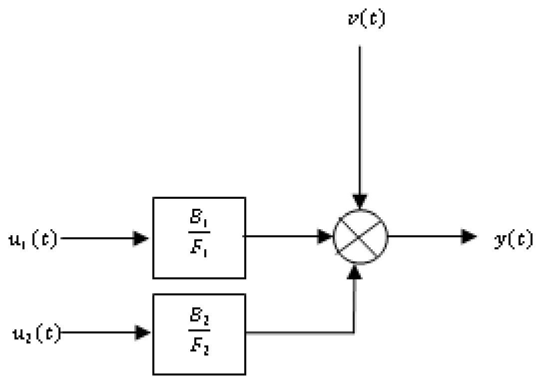

Figure 4 : the OE model structure

We present this structure in the following compact form:

$$y(t) = q^{-nk}\frac{B(q)}{F(q)}u(t) + v(t)$$

Polynomials F(q) and B(q) are given by:

$$F(q) = 1 + f_1q^{-1} + \ldots + f_{nf}q^{-nf}$$

$$B(q) = b_0 + b_1 q^{-1} + \ldots + b_{nb} q^{-nb}$$

$F(q)$ and $B(q)$ represent the parameters of the dynamic system, q^{-1} is the delay operator between the excitation and the response of the dynamic system, this description of is equivalent to the transform in Z [10], $f_1 \ldots \ldots f_{na}$ and $b_1 \ldots \ldots b_{nb}$ its polynomials parameters $F(q)$ and $B(q)$.

d) Box Jenkins model

The BJ model belongs to the class of output error models. This is an OE model with additional degrees of freedom for the noise model, while the OE model assumes a white additive disturbance at the output of the process, allowing BJ modelling of any disturbance. It can be generated by filtering white noise through an arbitrary numerator and denominator linear filter. The mathematical form of the structure of the BJ model is in the following compact form:

$$y(t) = q^{-nk} \frac{B(q)}{F(q)} u(t) + \frac{C(q)}{D(q)} v(t)$$

The polynomials of the BJ structure are defined by:

$$F(q) = 1 + f_1 q^{-1} + \ldots + f_{nf} q^{-nf}$$
$$B(q) = b_0 + b_1 q^{-1} + \ldots + b_{nb} q^{-nb}$$
$$C(q) = 1 + c_1 q^{-1} + \ldots + c_{nc} q^{-nc}$$
$$D(q) = 1 + df_1 q^{-1} + \ldots + d_{nd} q^{-nd}$$

The representation of the structure of the BJ model can be expressed as follows:

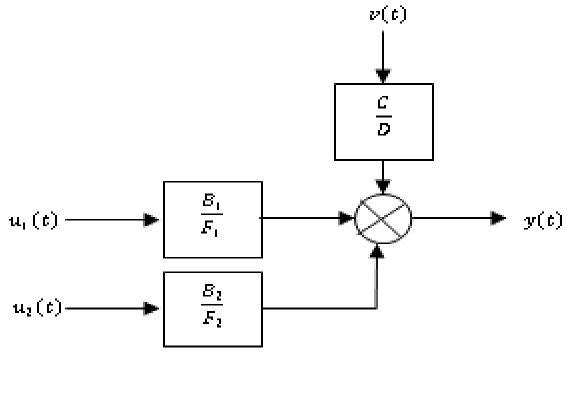

Figure 5: The Box Jenkins model structure

C. Estimation of parameters:

LTI model orders are usually determined using prior knowledge of the system or informative criteria. The interest is to minimize the variables d and θ.

$$min_{d,f} f(d, N) * \sum_{i=1}^{N} e^2(i, \theta)$$

where N is the number of data and d is the dimension of h (the number of estimated parameters). The structure of the chosen model should provide a compromise between the number of parameters and the fit of the model. Akaike's Information Criterion (AIC) is one of the methods used for this kind of system [17].

$$min_{d,f} f\left(1 + \frac{2d}{N}\right) * \sum_{i=1}^{N} e^2(i, \theta)$$

Or the Akaike criterion for final prediction error (FPE) is presented by the following equation [17].

$$min_{d,f} f\left(\frac{1 + \frac{d}{N}}{1 - \frac{d}{N}} * \frac{1}{N}\right) * \sum_{i=1}^{N} e^2(i, \theta)$$

To detect whether a given model structure is underestimated or overestimated [19, 18]. When several competing models are adjusted using the maximum likelihood method, the one with the lowest AIC value is chosen as the best model. This approach is, however, much more difficult in the case of LTV model structures, especially for time-varying logistic systems with multiple degrees of freedom [25], where many difficulties concerning the methods of autonomous model structure selection and parameter estimation have been reported [20]. Nevertheless, limited applications allowing simultaneous recursive estimation of several model structures have been reported in the literature [22,21].

D. Recursive estimation methods:

The general LTV model identification procedure is given by the following recursive algorithm, in which the current parameter vector $h(i)$ is updated according to the previous parameter vector $\theta(i-1)$.

$$\hat{\theta}(i) = \hat{\theta}(i-1) + k(i)e(i)$$

The error between the actual system output and the estimated model output is defined as follows:

$$e(i) = y(i) - \varphi^T(i).\hat{\theta}(i-1)$$

The generalized gain matrix K (i) is obtained by using the regression vector $u(i)$ and the covariance matrix $P(i)$ as:

$$K(i) = P(i) . \varphi(i)$$

The estimation of parametric model parameters used in this paper requires the formulation of a loss function as follows:

$$V_N(\theta) = \frac{1}{N} \sum_{i=1}^{N} e^2(i, \theta)$$

and minimize

$$\hat{\theta} = minV_N(\theta)$$

With the use of iterative search algorithms (for example, the Newton-Gauss) [22,23,24,21]. In the case of the ARX, ARMAX, OE and BJ models, the loss function is linear in the model parameters.

$$V_N(\theta) = \frac{1}{N} \sum_{i=1}^{N} e^2(i)$$

Once a series of input-output information is given, the model parameters are estimated using the least squares method. In addition, the recursive modelling technique is a fast technique for estimating model parameters after each sampling of a set of data. The validation of the model is the final step is a mandatory step to decide whether the identified model is accepted or not. [16] The purpose of model validation is to verify whether the identified model meets the modelling requirements for a particular application. To obtain a good estimated model, it is necessary to distinguish between the lack of fit between the model and the data due to random processes and, due to the lack of complexity of the model. In most statistical tools, the measure of the fit of a model is determined by the coefficient of determination [26].

$$R^2 = 1 - \frac{sumofsquaredresiduals}{totalsumofsquares} \text{ with } 0 \le R^2 \le 1$$

Retrieval Number:100.1/ijrte.A1585059120
DOI:10.35940/ijrte.A1585.119420
Journal Website: www.ijrte.org

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RMSE is used to evaluate a preacher's performance prediction, in the same way that the accuracy of prediction increases, as the mean squared error decreases [26].

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\tilde{y} - y)^2}$$

III. RESULTS AND DISCUSSION:

We used the parametric identification method discussed above to model the behaviour of the inventory level of a warehouse of a distribution company.

The external parameters of the warehouse are receptions and shipments while the output of the system is the stock level. For this we have analysed the data (inputs and outputs) it has been found that the warehouse consists of three families of articles: high rotation, medium rotation and low rotation items). In this paper we have studied the stock level for high turnover items while the medium and low rotation items will not be processed. The warehouse of this company is managed according to the following procurement policy: the receipts are calculated on the basis of the estimates of the department purchases and supplies, and the orders (shipping) are random (according to the demand of the customers), this which requires good inventory management. The method of supply followed for the management of this warehouse is an anticipation of the demand (the forecasts are not included in this study).

The warehouse will be considered as a MISO system (inputs: receptions and shipments, output: the level of the stock), for that we have proposed some hypotheses:

We have considered the stock as an invariant system over time (stock characteristics do not change over time).

We took the unit of time equal to one day.

After reception, items are entered into the management system and appear immediately on the system.

The input and output data were extracted from the warehouse information system (WMS).

Different data sets were collected from the Warehouse Information System (WMS) and entered into the System Identification Toolbox with a default software value of 1s of sampling in the MATLAB software. Since the system time constant was calculated as 1 day, 158 samples were collected for a period of 6 months. The data sets were used to obtain the mathematical model of the system for describing the dynamic behaviour of the stock level of the warehouse.

Different polynomial models have been estimated with a different order to obtain a better model with an optimal value. These models were ARX, ARMAX, OE and BJ.

The datasets were divided into two parts: the estimation data and the validation data. The estimation data is the data used to generate the mathematical model, while the validation data is used to ensure that the mathematical model is acceptable.

Figure 6 represent the data used in the estimation of the mathematical model of the stock level.

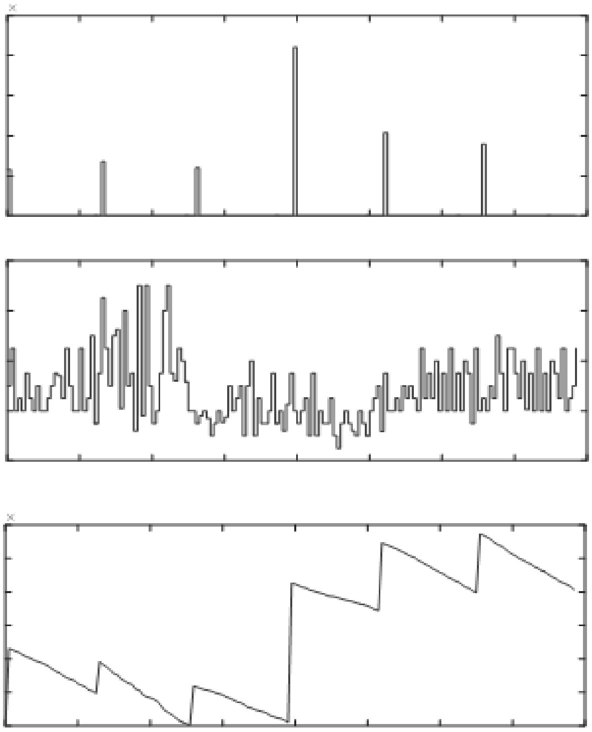

Figure 6 : Inputs and outputs of the warehouse system

After estimating the mathematical models of the system (stock level), we validated the mathematical equations of the models found with other datasets (Figure 7), we found the results shown in the tables below.

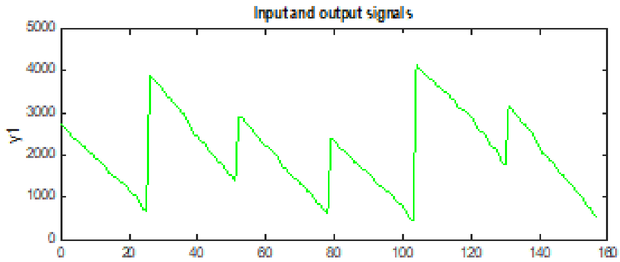

Figure 7: Inventory level for model validation

Table 1 : The best-fit values (in %) of the ARX models with different orders

	Validation 1		Validation 2
Model	BestFit(%)	FPE	Best Fit (%)
ARX[1 1 0]	72,1	$1,138*10^6$	-40,83
ARX[1 2 0]	62,94	$1,119*10^6$	-79,32
ARX[2 1 0]	60,6	$9,66*10^5$	-97,76
ARX[2 2 0]	65,15	$7,968*10^5$	-62,9
ARX[2 3 0]	69,57	$7,918*10^5$	-35,32
ARX[3 2 0]	95,59	$1,32*10^4$	63,61
ARX[3 3 0]	96,31	$1,294*10^4$	72,06
ARX[3 4 0]	96,15	$1,315*10^4$	69,79
ARX[4 4 0]	96,12	$1,348*10^4$	69,83
ARX[4 5 0]	96,29	$1,373*10^4$	71,15
ARX[5 5 0]	96,29	$1,408*10^4$	71,54
ARX[5 4 0]	96,14	$1,381*10^4$	70,48

Table 2 : The best-fit values (in %) of the ARMAX models with different orders

Model	Validation 1		Validation 2
	Best Fit (%)	FPE	Best Fit (%)
ARMAX[3 2 1 0]	97,33	$1,344*10^4$	96,94
ARMAX[5 4 1 0]	97,25	$1,419*10^4$	97,43
ARMAX[5 5 1 0]	97,24	$1,451*10^4$	97,63
ARMAX[4 4 1 0]	97,14	$1,633*10^4$	97,44
ARMAX[4 4 2 0]	97,14	$1,567*10^4$	97,48
ARMAX[4 3 2 0]	97,13	$1,376*10^4$	97,72
ARMAX[4 3 3 0]	97,11	$1,387*10^4$	97,76
ARMAX[5 3 1 0]	97,06	$1,402*10^4$	97,9
ARMAX[3 3 2 0]	97,01	$1,502*10^4$	97,89
ARMAX[3 3 1 0]	97	$1,338*10^4$	97,93

Table 3 : The best-fit values (in %) of the OE models with different orders

Model	Validation 1		Validation 2
	Best Fit (%)	FPE	Best Fit (%)
OE[3 4 0]	98,04	$4,294*10^4$	84,33
OE[4 5 0]	98,04	$4,658*10^4$	81,05
OE[5 1 0]	98,04	$4,213*10^4$	87,27
OE[2 3 0]	97,98	$4,243*10^4$	82,13
OE[1 2 0]	97,95	$4,056*10^4$	82,92
OE[4 1 0]	97,94	$4,411*10^4$	82,95
OE[3 3 0]	97,36	$7,446*10^4$	75,07
OE[2 2 0]	97,05	$8,583*10^4$	78,57
OE[5 5 0]	96,32	$1,658*10^5$	75,93
OE[4 4 0]	95,92	$1,909*10^5$	78,84

Table 4 : The best-fit values (in %) of the BJ models with different orders

	Validation 1		Validation 2
Model	Best Fit	FPE	Best Fit
BJ[2 3 3 3 0]	98,24	$1,381*10^4$	76,89
BJ[4 4 4 4 0]	98,04	$1,44*10^4$	38,12
BJ[5 5 5 5 0]	98,01	$1,542*10^4$	77,14
BJ[2 2 2 2 0]	97,98	$1,381*10^4$	73,92
BJ[1 1 1 2 0]	97,83	$1,283*10^4$	70,35
BJ[3 3 3 4 0]	97,62	$1,882*10^4$	89,23
BJ[4 5 5 5 0]	97,39	$1,48*10^4$	70,35
BJ[4 4 4 5 0]	97,28	$1,945*10^4$	60,94
BJ[3 4 4 4 0]	97,06	$1,578*10^4$	38,12
BJ[2 2 2 3 0]	97,06	$1,381*10^4$	64,91

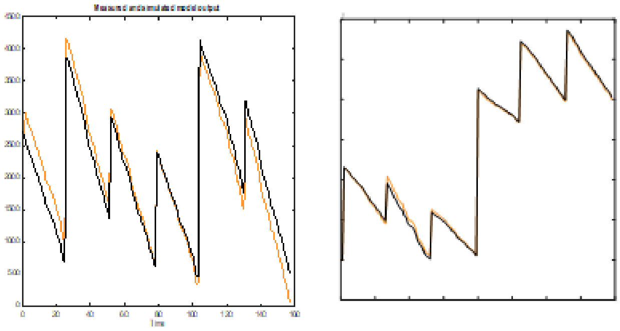

Figure 8: validation ARX model

After estimating the different models with multiple levels (1 to 5), we found that all the models have very good satisfaction and provide mathematical models that simulate the behaviour of the system (stock level) with similarities rate exceeding 95% (ARX: 96.31%, ARMAX: 97.33%, EO: 98.04% and BJ: 98.24%). In this case the choice of the right model will be based on the number of parameters put into play (poles and zeros) and the level of FPE.

Table 5 : Estimation results for all models

Models	Nbrof parameters	Best Fit (%) validation 1	Best Fit (%) validation 2	FPE	Characteristics (poles and zeros)
ARX	6	96,31	72,06	$1,294*10^4$	3 poles 3 zeros
ARMAX	6	97,33	96,94	$1,344*10^4$	3 poles 3 zeros
OE	7	98,04	84,33	$4,294*10^4$	3 poles 4 zeros
Box Jenkins	11	98,24	76,89	$1,381*10^4$	6 poles 5 zeros

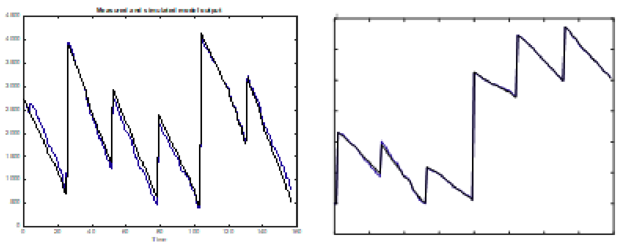

Figure 10: validation OE model

The table above shows that the ARMAX model gives a good estimate for both validation data and a lower MER than the models (OE and BJ), while the BJ model gives the best estimate with 98,24 and one FPE of 1.381*104 but the number of parameters far exceeds the other models (11 parameters), the ARX model gives a good estimation report for the first data set but the estimate for the validation data 2 gives 72.06 % as best fit, so the ARX model is only applicable for the first system only, the OE model gives good estimates for both systems, but its FPE is very high compared to other models. For the present system we will choose the ARMAX model, because its best fit for both systems exceeds 95% and its FPE is smaller compared to other models.

IV. CONCLUSION

A warehouse management system has been analysed and identified. Several sets of data were collected and analysed. System identification was used to develop mathematical models describing the dynamic behaviour of the system. For this system, the inputs were receptions and shipments while the output was the stock level. Several model structures (ARX, ARMAX, OE and BJ) with different orders have been developed to describe the dynamic behaviour of the system. The results of the simulation revealed that the ARMAX models are the most suitable model for this system, while the OE, BJ and ARX models gave good results but with some disadvantages (high order, high EPF or lower estimate for data from the second validation. So, the ARMAX model has been accepted for modelling this system because it offers a good fit best for both validation data and a reduced FPE.

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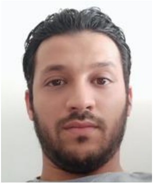

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