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# An Investigation of Stochastic Analysis of Flexible Manufacturing Systems Simulation

W. H. Ip[1], R. Fung[2] and K. W. Keung[1]

[1]Department of Manufacturing Engineering, the Hong Kong Polytechnic University, Kowloon, Hong Kong; and [2]Department of Manufacturing Engineering and Engineering Management, the City University of Hong Kong, Hong Kong

*This paper describes the use of an ARIMA (autoregressive-integrated-moving-average) model and its equivalent state space models to produce rule-based knowledge for flexible manufacturing systems (FMS) that can be used to investigate a wide variety of problems including machine breakdown, material shortage, and changes of scheduling rules. One great advantage of using the proposed models is the ease with which the simulation results can be summarised, analysed and captured, as well as the availability of the mathematical representation of the knowledge that can be kept in a knowledge database for evaluation and selection of alternative FMS strategies in a real-time environment. Various case studies are used to illustrate the methodology and the development of ARIMA and state space models, the analysis includes the system cost and stability of changes or interventions, the relationships among the simulation inputs and outputs, and the formulation of the production rule-base for the FMS scheduler. Management can use this integrated approach to describe and predict the dynamic behaviour of a complex FMS.*

**Keywords:** ARIMA; FMS simulation; Scheduling rules; State-space; Transfer functions

## 1. Introduction

Flexible manufacturing systems (FMS) are computer-controlled batch-manufacturing systems which combine the efficiency of mass production with the flexibility of job shops. An FMS consists of numerically-controlled (NC) machines, automated material-handling mechanisms, robots, and in-process storage facilities. An FMS operates in a large variety medium-volume production environment and is usually designed to produce a variety of high-precision parts and products. There are many complex issues associated with the design of an FMS. Scheduling is one of the most difficult aspects of FMS operations. During FMS operations, it is necessary to determine which of the required jobs is to be carried out by which machine. For example, the system must decide the most appropriate means of transportation; must select the equipment, the machine tools, the vehicles, the pallets, and the fixtures; and must monitor the progress of the workpieces and the orders. Furthermore, in the case of an interruption in the FMS owing to machine breakdown, it is important to choose an alternative to adapt to the new situation. Various approaches to the scheduling problems can be seen in [1–5]. Recent research [4,6] suggested the use of priority rules which can be classified as local or global, static or dynamic. Local rules are derived exclusively from information relating to a particular FMS resource such as a machine centre, whereas global rules are based on any relevant information about the state of the entire FMS. Static rules arise from information that is independent of the particular state of the system at any given time, but dynamic rules, in contrast, process the most recent information available regarding the state of the system. Dynamic rules can be further distinguished based on whether their parameters change on the basis of past values. This is a research area that has attracted much interest. Various authors have attempted to use techniques such as expert systems and artificial intelligence to represent FMS knowledge [7–9]. In this investigation, a non-traditional approach is used, the dynamic rules being identified using time series models which enable the interrelationships that persist over time to be found. Box and Jenkins [10] and Box and Tiao [11] provided a time series modelling approach which can be used to analyse the interruptions and the FMS system dynamics. Applications of their modelling approach in solving management and production line problems can be found in [12–14].

*Correspondence and offprint requests to*: Dr W. H. Ip, Department of Manufacturing Engineering, The Hong Kong Polytechnic University, Kowloon, Hong Kong. E-mail: mfwhip@polyu.edu.hk

## 2. FMS Model

The FMS model currently under consideration is designed to manufacture metal blocks. Basically, the FMS consists of an automated storage and retrieval system (AS/RS), a material handling system, a set of computer controlled machining centres, two inspection devices and a set of computers to control all the operations within the FMS. Figure 1 is a schematic diagram of the FMS model.

First, raw materials are stored in the AS/RS which is used to accomplish a storage transaction, delivering loads from the input station into storage, or retrieving loads from storage and delivering them to the output station. Then, the raw stock to be processed is delivered to the conveyor system. This conveyor will run as a loop with stops as a buffer in order to transfer the raw stocks and parts between the AS/RS, machining centres and the inspection devices. The raw stock will then be transferred to the "CodeTag" inspection device to verify that the correct material is being retrieved from the AS/RS. Connecting the conveyor system and the machining centres are two robots. Their role is to transfer the material from the conveyor into the machining centre or vice versa. After that, the raw stock is machined and processed by the NC lathe and milling machining centres into finished component. Another inspection location uses a vision device to inspect the features of the finished components. Finally, the finished components will be transferred back to the AS/RS by the conveyor.

The brain of the FMS is the system controller. This system controller is a set of computers with an attendant worker who keeps track of performance and intercedes when necessary to change priorities or solve problems. There are three levels for the hierarchy of the system controller. The bottom level are the machines and devices which are linked physically to the middle level – the two cell computers (Cell 1 and Cell 2). In this FMS, the CodeTag, the conveyor, robot1 and the NC lathe machining centre are linked to the Cell 1 computer and the AS/RS, vision system, robot2 and the NC milling centre are linked to the Cell 2 computer. The middle level is connected to the top level – the host computer.

The simulation model is constructed using WITNESS [15], which contains a set of data structure for the FMS and the associated logic for extracting and retrieving data. The major component in this WITNESS model includes several scheduling rules, which are typical scheduling rules in FMS (see [5]), and may be summarised as follows. SPT (LPT): shortest (longest) processing time; TOT: total processing time; SRPT (LRPT): shortest (longest) remaining processing time; FRO(MRO): fewest (largest) number of remaining operations; FIFO: first in, first out; SLACK: least amount of slack; EDD: earliest due date; CR: critical ratio and Random.

These are the typical scheduling rules in FMS, which can be static (used for off-line scheduling and resulting in a fixed schedule for the period), or dynamic (used for real-time scheduling which changes over time). Three major types of interruption are also included in the analysis: machine breakdown; machine shortage, and priority jobs. Figure 2 illustrates the proposed system architecture.

The performance of the system is measured by three major criteria:

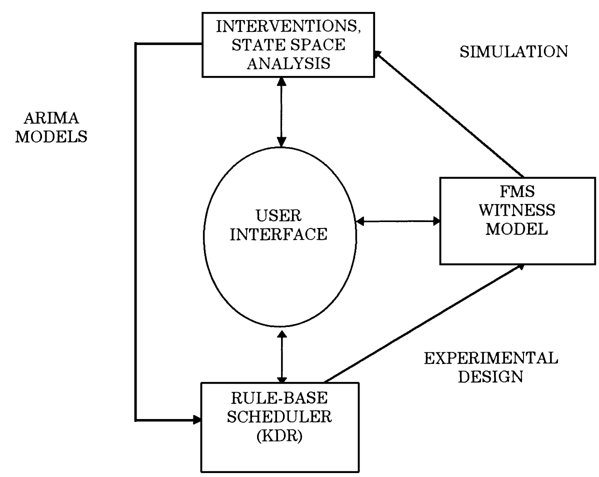


**Fig. 2.** System architecture of the rule-based ARIMA models for FMS.

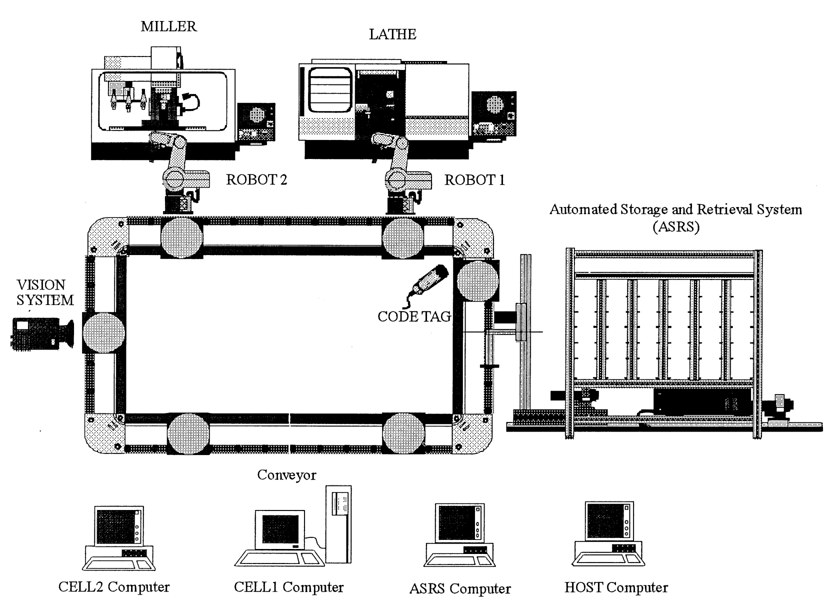


**Fig. 1.** Schematic diagram of the FMS model.

1. Time in the system, which is the time that the job spends in waiting and processing.
2. System use, which is the average percentage of time that the machines are busy.
3. The number of jobs in the system, which is the jobs in the system during the simulation study.

The time in the system $W$ and the use in the system $U$ are selected as the major dependent variables or performance measurements. The time in the system can be used to control and predict the optimal condition of the FMS schedule, and the use in the system can be used to estimate the effect of machine breakdown or material shortage. The number of jobs in the system, although important, is not expected to change significantly in the long term, and is therefore not analysed. Specifically, the behaviour of three major types of interruption is investigated: change of scheduling rules; machine breakdown; and material shortage.

## 3. Transfer Function Models

### 3.1 Intervention Modelling

The modelling to analyse the dynamic interruptions and changes of scheduling rules is performed using ARIMA models, which are described briefly as follows:

The general transfer model is of the form:

$$Y_t = \sum \frac{\omega_j(B)}{\delta_j(B)} B^{bj} X_{jt} + \frac{\theta(B)}{\phi(B)} a_t \quad (1)$$

where $Y_t$ is the output series, $X_{jt}$ is the input series, $\omega_j(B)/\delta_j(B)$ is the transfer function polynomial, $bj$ is the delay for the $j$th series, $\theta(B)/\phi(B)a_t$ defines the ARIMA noise model, and $a_t$ is a white noise function series.

An intervention models proposed by Box and Tiao [11] is of the form:

$$Y_t = \sum \frac{\omega_j(B)}{\delta_j(B)} B^{bj} I_{jt} + \frac{\theta(B)}{\phi(B)} a_t \quad (2)$$

where $I_{jt}$ is a binary or dummy variable (0,1) which is non-zero only during the period of intervention. To develop the model of Eq. (2), an univariate analysis on $Y_t$ is performed, which results in an ARIMA$(p,d,q)$ $(P,D,Q)^s$ autoregressive integrated moving average of the general form:

$$\nabla d \nabla D_s Y_t = \{\theta_q(B)\phi_Q(B^s)/$$
$$\phi_p(B)\Omega_P(B^s)\}a_t \quad (3)$$

where $\nabla_d$ is regular difference; $\nabla D_s$ is the seasonal differencing; $p$ is the number of autoregressive (AR) terms; $q$ is the number of moving average (MA) terms; $P$ is the number of seasonal AR terms and $Q$ is the number of seasonal MA terms.

The values of the parameters obtained in the univariate ARIMA model estimation, Eq. (1), are used as initial estimates of the parameters in the intervention model, Eq. (2). Different types of transfer function can be chosen to fit the response to the intervention variables. Once a tentative model is identified, it is followed by the estimation of parameters and diagnostic checks of residuals.

### 3.2 Univariate Transfer Function Modelling

For a single input $X_t$, the transfer function can be simplified into:

$$Y_t = V(B)\, X_t + N_t \quad (4)$$

Where,

$$V(B) = \omega(B)^b/\delta(B)$$
$$\omega(B) = \omega_0 - \omega_1 B - \ldots - \omega_s B^s$$
$$\delta(B) = 1 - \delta_1 B - \ldots - \delta_r B^r$$
$$N_t = \theta(B)/\phi(B)a_t$$

The development of the transfer function is outlined as follows:

1. Identify and estimate the model for input $X$. An univariate analysis on $X_t$ is performed using the autocorrelation (ACF), partial autocorrelation (PACF) and inverse autocorrelation (IACF). It results in an ARIMA$(p,d,q)$ $(P,D,Q)^s$ autoregressive integrated moving average of the general form of Eq. (2) or Eq. (3).
2. Pre-whiten both $X_t$ and $Y_t$. The output series is next pre-whitened using the univariate model of input $X$. The pre-whitening process is performed as follows:

   If $\theta(B)X_t = \phi(B)\, a_t$, and if we define

   $Y_t' = \{\theta(B)/\phi(B)\}Y_t$; $X_t' = \{\theta(B)/\phi(B)\}X_t = a_t$

   Computing $Y_t'$ and $X_t'$ from the univariate model $X$ is known as "pre-whitening". In addition, the cross-correlation between $X_t'$ and $Y_{t+j}'$ are proportional to $V(B)$ which is also known as the impulse response function.
3. Identify the appropriate transfer function form using the cross-correlation function. The cross-correlation function (CCF) is most important in determining the form of the transfer function, i.e. $\omega(B)$, $\delta(B)$, and $b$. The transfer function is restricted to workable functional forms according to the result of the analysis of CCF. The identification of $r,s,b$ is accomplished by observing and comparing the impulse response weights generated by the theoretical transfer functions.
4. Fit the transfer function followed by residual analysis. After the form of the transfer function model has been determined, a model for the noise component must be specified. This is done by using the ACF, PACF and IACF of the residual, and specifying an appropriate univariate model.
5. Fit the transfer function-noise model. Combing the transfer function model and noise model leads to

$$Y_t = \omega(B)/\delta(B)X_{t-b} + \theta(B)/\phi(B)a_t \quad (5)$$

### 3.3 State Space Modelling

Models in ARIMA representation can be put into state space form in a systematic way; conversely, models in state space representation can be put into ARIMA representation. Theoretically, then, models in these two alternative representations are equivalent; Akaike [16] demonstrated the equivalence of the two approaches. If we define $X_t$ as the multivariate vector of state variables at time $t$, the state space model consists of a transition equation and an observation equation as follows:

$$X_t = FX_{t-1} + G\xi_t, \text{ transition equation} \tag{6}$$

where $X_t$ is a sequence of normally distributed white noise with known or an otherwise defined covariance structure representing the manner in which the state will be allowed to change. $F$ is the transition matrix and $G$ is the input matrix. Then

$$Y_t = HX_t + \epsilon_t, \text{ observation equation} \tag{7}$$

where $Y_t$ is a function of the state variables and $\epsilon_t$ is a sequence of normal white noise representing the error in the observation and $H$ is the observation matrix. Akaike [16] has introduced a statistical vector model identification procedure that can be conducted automatically. Given the vector of observations $Y(t)$, we wish to determine the optimal order $m$ such that at time $t$, all significant past and present information is contained in $Y(t), Y(t-1), \ldots, Y(t-m)$. This is done by successively increasing the order of vector autoregression:

$$Y(t) = \theta_1 Y(t-1) + \theta_2 Y(t-2) + \ldots + e_t$$

and computing the following Akaike's information criterion, (AIC) [17] after each autoregressive fit:

$$\text{AIC}_i = n \log|C_i| + 2ik^2$$

where $n$ is the number of observations $|C_i|$ is the determinant of the $k$-dimensional covariance matrix. Akaike uses a series of canonical correlation analyses to determine the state vector $X_t$. The canonical correlation analyses between the present and past of the process:

$$Y^p = \{Y(t)', Y(t-1)', \ldots, Y(t-m)'\}'$$

and the set of present and future values:

$$Y^f = \{Y(t)', Y(t+1)', \ldots, Y(t+n)'\}'$$

they are used to determine the state vector $X_t$ and the $F$ and $G$ matrices. The order $m$ is determined by the minimum AIC in the stepwise autoregression. Stepwise canonical correlation analysis is performed between the fixed set $Y^p$ and $Y^f$ as the dimension of $Y^f$ increases. At each step the last canonical correlation is tested for significance by the differenced information criterion (DIC) which tests the components of the state vector for linear dependence. A negative value of the criterion indicates linear dependence of the last element entered into the state vector. The preliminary estimates for the parameters of the $F$ and $G$ matrices are obtained from the canonical correlation analysis and these estimates of the matrix parameters are then used to obtain an infinite AR representation which in turn is used to obtain a sample estimate for the residual covariance matrix $G$. Once the state vector model has been identified, a complete set of Kalman filtering equations [18] are developed for model prediction and control.

## 4. Case Studies

The FMS scheduling rules described earlier are used to form the intervention models. The first example of interruption or intervention is generated by the change in the random scheduling rule to the shortest processing time scheduling rule. $Y_t$ represents the FMS performance measurement which is the waiting time in the system and $I_t$ is the intervention or changes. The intervention was initiated at the 100th period. ARIMA identification using autocorrelation (ACF), partial autocorrelation (PACF) and inverse autocorrelation (IACF) functions indicates a model of three AR factors and a differencing of two periods.

The pre-intervention model using the random scheduling rule is:

$$(1 - B^2)Y_t = \frac{a_t}{\{(1 - 0.3727B)(1 + 0.5792B^2)(1 + 0.5056B^4)\}}$$

The post-intervention ARIMA model after changing to the shortest processing time scheduling rule is estimated, where the diagnostic of residuals indicates that it is a white-noise process. The model which includes the intervention is:

$$(1 - B^2)Y_t = \frac{-16.32I_{t-8}}{(1 - 0.8244B)} + \frac{a_t}{\{(1 - 0.284B)(1 + 0.579B^2)(1 + 0.507B^4)\}}$$

The asymptotic change given by the intervention in the scheduling rule is

$$16.32/(1-0.8244) = 93 \text{ units.}$$

The second example analyses the intervention of the shortage material. $Y_t$ measures the utilization and $I_t$ is the intervention due to material shortage. ARIMA identification of ACF, PACF and IACF indicates a model of AR(2).

The pre-intervention model before material shortage is:

$$Y_t = 644.7 + \frac{a_t}{(1 + 0.604B^2)}$$

The post-intervention ARIMA model after material shortage occurs is estimated, where the diagnostic of residuals indicates that it is a white-noise process. The model which includes the intervention is:

$$Y_t = 644.7 - 137.9I_{t-5} + \frac{a_t}{(1 + 0.604B^2)}$$

The following interpretations can be drawn from the two models. In the first model, the change of scheduling rule from random to shortest operation time is estimated by an initial decrease of 16.32 units and is followed by an alternative increase and decrease to a permanent level. The intervention effect can be calculated as an asymptotic change of 93 units. The lag time effect is estimated to be 8 periods before the system settles down to a steady state. In the second model, the intervention due to material shortage has an immediate effect, which decreases the system use to 138 units, the time lag effect being 5 periods.

It can be seen that the form of the intervention is changed by a combination of the numerator and denominator of the intervention component. When the parameter in the denominator is large, the intervention effect is realised slowly, whereas when it is zero the effect is realised instantaneously. The parameter is limited to the interval of −1 to +1: if it lies outside this range the intervention becomes unstable. The result of the analysis agrees with the expectation that the scheduling rule using the shortest operation time performs better than a random method. The shortage of material will certainly decrease the system use. The models provide a precise estimation of the form and magnitude of the intervention effects on the FMS. The interpretation and analysis reveal the transient behaviour of FMS interventions and provide the answers for FMS analysts regarding the effects of changing the scheduling rules and the interruption of material shortage. Similar analysis can be done to model the effects of other scheduling rules such as the critical ratio and FIFO, as well as for the interruptions by machine breakdown and re-scheduling of the priority of jobs. It should be pointed out that these analyses could not be accomplished by steady-state analysis such as ANOVA, because the successive FMS simulations are correlated and the noise factor is not isolated.

In the second example, we apply the transfer function modelling technique described in Section 3.2 to analyse the FMS simulation. Here, the FMS simulations are generated by the work orders and the output is the system costs, the system control rule is FIFO. On the assumption that there is no feedback, we built a model of the transfer function to represent the behaviour of the system. We first identified a model describing the work order which is used to prewhiten $X_t$ and $Y_t$. The univariate model of $X_t$ was identified using ACF, PACF and IACF which indicated a model of two AR factors. The identification, estimation and diagnostics suggested that the model was adequate.

The model for the demand is

$$X_t = \frac{a_t}{(1 - 0.372B + 0.507B^2)}$$

Once we obtained the model describing $X_t$, we used this model to prewhiten $X_t$ and $Y_t$. The prewhitening filter required a further differencing of eight periods. The sample cross-correlation (SCC) indicated that they were not white noise, and we noted that the lag at which we encountered the first spike in the SCC is zero. The SCC appeared to die down in a sinusoidal pattern after lag zero. We set $b = 0$, $r = 2$ and $s = 0$. The tentative model is of the form:

$$(1 - B^8)Y_t = \frac{\omega_0(1 - B^8)X_t}{(1 - \delta_1 B - \delta_2 B^2)} + N_t$$

Further analysis of the residual sample correlation (RSC) indicated that the residual was not white noise. To find a model describing $N_t$, we applied two AR factors at lag 10 and lag 13 and another AR factor at lag 8. The final model is;

$$Y_t = \frac{1.6X_t}{(1 + 0.73B + 0.5B^2)} + \frac{a_t}{(1 - B^8)(1 - 0.18B^{10} - 0.16B^{13})(1 + 0.49B^8)}$$

The third case illustrated the use of state space modelling. In this example, the FMS simulation output is generated by the demand, the lot size rule was CR (critical ratio). State space models allowed feedback, and both the demand and system cost can be treated as input variables or exogenous variables and modelled simultaneously. However, in this simulation analysis, we treated the work order as the input and the system cost as the output. The ACF and PACF of the demand pattern died out, which indicated that it was nearly stationary. The ACF and PACF of the system cost died out slowly which required further differencing and transformation to stationary. It was deseasonalised by an ARIMA(1,1) model in the seasonal lags. The seasonal effects of the output were hence removed before analysis. The identification and estimation of the state space model were performed using the AIC criterion and a number of important statistics. They were summarised in the following:

| | Trial order | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Criteria | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| AIC | 872.7 | 871.1 | 860.5 | 853.6 | 834.8 | 844.4 | 846.0 | 842.8 | 842.3 |
| Schwarz | 842.2 | 857.6 | 861.9 | 868.0 | 864.6 | 880.3 | 890.8 | 897.7 | 906.1 |
| FPE | 834.7 | 842.7 | 839.6 | 838.4 | 827.8 | 836.3 | 839.5 | 839.5 | 841.1 |

To determine the model order, the order which minimises the criteria was chosen. Each criterion decreases as the error variance decreases or goodness-of-fit increases, but increases as the number of parameters increases. There were a wide variety of criteria which differ only in the manner and degree to trade off between goodness-of-fit and complexity based on the AIC criterion. The first term of AIC is a goodness-of-fit and the second is a penalty for complexity of the model. The Schwarz error criteria [19], on the other hand, penalises complexity to a much higher degree, which leads to models of lower order than AIC. The final prediction error (FPE), which is calculated as the variance of the one-step-ahead prediction errors in the model, is another measure of the goodness-of-fit. The criteria suggested that a model of order five would be appropriate. Further analysis of the residual correlation, however, indicated that there was autocorrelation at a particular lag and an order of seven was chosen. The transition matrix $F$, input matrix $G$ and Kalman gain matrix $K$ were estimated as follows:

Transition matrix $F$

| | | | | | | |
|---|---|---|---|---|---|---|
| 0.0000 | 1.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| 0.0000 | 0.0000 | 1.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| 0.0000 | 0.0000 | 0.0000 | 1.0000 | 0.0000 | 0.0000 | 0.0000 |
| 0.0000 | 0.0000 | 0.0000 | 0.0000 | 1.0000 | 0.0000 | 0.0000 |
| 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 1.0000 | 0.0000 |
| 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 1.0000 |
| −0.1641 | 0.5811 | −0.9007 | 0.6262 | −0.1065 | −0.8390 | 1.5977 |

| Kalman gain matrix $K$ | Input matrix $G$ |
|---|---|
| −0.1108 | 0.8621 |
| 0.2473 | −0.2372 |
| −0.1168 | 0.2218 |
| 0.0852 | −0.3659 |
| −0.1374 | 0.2096 |
| 0.0523 | −0.0772 |
| −0.1702 | 0.3116 |

Prediction matrix $H$

1.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000

The equivalent Box–Jenkins ARIMA($n$,$n$) model can be expressed as

$$Y_t = \omega(B)/\delta(B)X_t + \varphi(B)a_t \text{ or alternatively,}$$

$$Y_t(1 - \delta_1 B^1 - \ldots - \delta_n B^n) = X_t(\omega_1 B^1 + \omega_2 B^2 + \ldots + \omega_n B^n) + a_t(1 - \varphi_1 B^1 - \varphi_2 B^2 \ldots + \varphi_n B^n)$$

Where the autoregressive matrices $\delta_1,\ldots,\delta_n$ are the same as in the $F$ matrix, and the $\varphi_1\ldots,\ \varphi_n$ and $\omega_1,\ldots,\ \omega_n$ can be computed recursively as follows:

$$\varphi_1 = K[1]-\delta_1$$
$$\varphi_2 = K[2]-\delta_1 K[1]-\delta_2$$
$$\varphi_3 = K[3]-\delta_1 K[2]-\delta_2 K[1]-\delta_3$$
$$\varphi_n = K[n]-\delta_1 K[n-1]-\delta_2[n-2]\ldots-\delta_n$$
$$\omega_1 = G[1]$$
$$\omega_2 = G[2]-\delta_1 G[1]$$
$$\omega_3 = G[3]-\delta_1 G[2]-\delta_2 G[1]\ldots$$
$$\omega_n = G[n]-\delta_1 G[n-1]\ \ldots\ -\delta_{n-1} G[1]$$

The ARIMA model is therefore

$$Y_t(1-1.598B+0.839B^2+0.106B^3-0.626B^4+0.900B^5-0.581B^6+0.164B^7)=$$
$$X_t(0.862B-1.615B^2+1.324B^3-0.827B^4+0.415B^5+0.229B^6-0.282B^7)+$$
$$a_t(1-1.708B+1.263B^2-0.498B^3-0.158B^4+0.625B^5-0.504B^6+0.164B^7)$$

The adequacy of the fitted state space model was checked by examining various statistics including the Ljung–Box test and $R$-squared. Other similar tests were the Durbin–Watson test and the $F$-test, which also indicated that the model was adequate. The autocorrelations of the 12 lagged residual errors were as follows and none of the autocorrelations exceed two standard errors and there is no evidence to assume inadequacy in the model:

Autocorrelations of lagged residual errors

| Lag: | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | −0.01 | −0.13 | −0.14 | −0.21 | 0.09 | 0.12 | −0.03 | −0.01 | −0.06 | −0.03 | 0.19 | −0.14 |

## 5. Conclusion

There are two purposes for the use of ARIMA models. First, the ARIMA model is inserted into a knowledge data representation (KDR) in order to provide knowledge about the behaviour of the FMS that is represented in Fig. 2. The second purpose is to provide the decision maker with this set of rules or interruptions which represent insight about the system so that better decisions can be made in the future. The methodology is the logical extension of the scheduling rules in FMS. Here, the FMS specific knowledge, based on past simulation, is stored in the form of knowledge. When a decision has to be made, it is possible to explain a particular state of the FMS with the help of the ARIMA models captured and also to derive an alternative strategy for FMS planning and control. Conventional knowledge representation is characterised by its inflexibility and lack of specific domain knowledge about a particular FMS interruption. The methodology proposed here is data driven in a parametric sense, the FMS simulation being used to construct the knowledge base and the interruption being captured through the ARIMA models. Moreover, it is a systematic methodology of identification, estimation and diagnostics of the residuals in developing and integrating simulation with rule-based knowledge for FMS. The methodology provides a sound theoretical basis for the analyst in modelling dynamic response. The requirements for applying the methodology successfully are:

1. A detailed knowledge of FMS problems.
2. An understanding of the theoretical principles and applications on which time series analysis is based.
3. An appreciation of the practical analytical skills that are necessary to develop and use the methodology.

By constructing models which contain the skill judgement, production scheduling rules and knowledge of the underlying FMS, machines and processes descriptions; and by first-principle reasoning; a powerful and flexible system can be built. The system is capable of generating realistic and accurate descriptions of FMS and has been shown to provide considerable promise for the solving of complex FMS scheduling problems. This paper has demonstrated the use of an ARIMA model to produce rule-based knowledge for FMS that can be used to investigate a wide variety of problems including machine breakdown, material shortage, and changes of scheduling rules. The ARIMA model represents the underlying mechanisms of the FMS and increases the understanding of the dynamic behaviour of the system. The methodology has been extended further to the study of multivariate stochastic processes of FMS, one great advantage of using ARIMA analysis being the ease with which the simulation results can be summarised, analysed and captured. Moreover, the importance of this approach is the mathematical representation of the knowledge that can be kept in a knowledge database for the evaluation and selection of alternative FMS strategy in a real-time environment.

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