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Faults Forecasting System

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***Abstract*—**This paper presents Faults Forecasting System (FFS) that utilizes statistical forecasting techniques in analyzing process variables data in order to forecast faults occurrences. FFS is proposing new idea in detecting faults. Current techniques used in faults detection are based on analyzing the current status of the system variables in order to check if the current status is fault or not. FFS is using forecasting techniques to predict future timing for faults before it happens. Proposed model is applying subset modeling strategy and Bayesian approach in order to decrease dimensionality of the process variables and improve faults forecasting accuracy. A practical experiment, designed and implemented in Okayama University, Japan, is implemented, and the comparison shows that our proposed model is showing high forecasting accuracy and BEFORE-TIME.

***Keywords*—**Bayesian Techniques, Faults Detection, Forecasting techniques, Multivariate Analysis.

I. INTRODUCTION

CHEMICAL processes and their control systems have become very complex due to product quality demands, safety levels, operational constraints, environmental regulations, and plant economics. As a result, many researches are upward development of more techniques and systems to facilitate and safely do process monitoring and control.

Faults Detection is considered one of the main concerns in process monitoring. Due it is costing the industry a lot, when undetected fault happens. There are a lot of faults detection systems in historical research papers, some of them were depending on statistical methods such as in [16], [9], others were depending on neural networks and fuzzy systems [24], [14]. But all are testing the current status weather it is fault or not, but not looking for future. So forecasting faults is a new idea we propose in this research work. It proposes that we analyze the history status for the process variables with the relation to faults occurrences and human inputs as expert opinion and predict when and where faults are going to happen. We assume that product cycles are repeated over time. So that makes it applicable to apply forecasting techniques on it. That supports operators and engineers to take pre-actions to avoid faults occurrence.

Forecasting must predict the future; hence this difficult task needs that methodology uses as much information as possible before issuing predictions. Past and current data related to what is needed to be forecasted, in this case faults variables, are certainly helpful and needed. Expert judgment can also be a valuable source of information [22]. Data, judgment, and uncertainty are relevant to most forecasting tasks, and should be incorporated into forecasting techniques.

In faults forecasting problems, there are large numbers of variables, process variables, and relationships among them that may be viewed as potentially important, leading to complex knowledge structures. Most traditional forecasting techniques apply sophisticated mathematics to relatively simple knowledge structures and may impose restrictions on the types of inputs that can be used. In contrast, modern computing makes it possible to unlock the intricacies of complex knowledge structures using only simple mathematics. Moreover, the simplicity of individual relationships within these complex networks allows the model to capture the multiple types of data that populate many domains.

Due to the complexity of the real data explained above, so we need to use methods which are able to deal with huge number of parameters. Building up big structural models incrementally equation by equation has been criticized on theoretical as well as on empirical grounds [10]. As far as the forecasting performance of these models is concerned, simple univariate ARIMA models seem to be superior or at least equivalent [22]. An alternative proposed by Sims in [3] is to build vector autoregressive models with no a priori exclusion restrictions. This methodology however quickly exhausts the available degrees of freedom, since each variable has to appear in each equation with the same lag specification. The scarcity of observations relative to the number of parameters to be estimated brings up the problem of over parameterization, and the test statistics as well as the forecasts of these models tend to deteriorate rapidly [8].

The proposed system combines two ways to overcome this difficulty. The first one is to start out with the unrestricted vector autoregressive model and to use the concept of Wiener-Granger causality see [4] to reduce the dimensionality of the model. This procedure is similar in spirit to the 'general-to-specific' approach of [18] in that it tests which variables contribute significantly to the precision of forecasting and excludes all other variables. Since the pre-test estimator has been shown to be statistically inferior to Stein rules [1]], it is tempting to contrast this approach in its forecasting

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performance with Bayesian point of view [2]. This is done by taking the unrestricted vector autoregression system and combining the sample information with prior information on the parameters and their standard errors.

This article is organized as follows: Section II provides the data and their transformations. The next two sections present the construction of the restricted and the Bayesian vector autoregressive model. Then the proposed model is proposed in Section V. Section VI explains the experiment with results. The last section summarizes conclusion and outline future work.

II. DATA

This research work proposes to analyze and forecast faults factors parameters which are process variables of the monitoring control process. As known for chemical control systems we have many types of process control data such as level, temperature, pressure,... Usually these systems are very complex and contain hundreds of control variables, which make it so difficult to forecast or predict faults occurrences with high accuracy. Usually there are Distribution Control systems which are connected to the system and monitor these process variables.

III. RESTRICTED VECTOR AUTOREGRESSIVE MODEL (RVAR)

Unrestricted VAR model was initially proposed by Sims in [3]. It is likely to lead many separately insignificant parameters, so that the search for restrictions which reduce the dimensionality of the model seems to be a rewarding task. This is especially motivated by a possible disturbing influence of insignificant parameters on forecasting.

There is no unique way for setting up such restrictions. In many cases, they are based on information extracted from theory concerning the structure and interaction of the time series. An alternative is the specification of restrictions on empirical grounds, which is based on the following procedure:
1) An unrestricted time series model is estimated. F- and t-statistics are noted. Those test the influence of one variable and a specific lag on another variable, respectively.
2) Insignificant variables and insignificant lags of variables are eliminated. The significance level was set to loosely to 15% to reduce the possibility of neglecting significant regressors which might be increased due to multicollinearity.
3) The resulting model, that is, an autoregressive model with zero restrictions, is estimated and used for forecasting.

Applying the procedure outlined above reduces the number of by more than 60% of the original number. The set of regressors in the restricted model (RVAR) depends on the search strategy [20]. A comparison of all possible subset models, as suggested by [21] would be rather tedious and time consuming. Anyway, the RVAR should not be ‘far away’ from the optimal model.

A variable is said to cause another one if and only if its lags reduce the forecasting variance additionally to the proper lags of the variable to be forecasted. Accurate significance levels, however, are not valid due to the iterative elimination process. Influences which are quicker than one quarter of a year are not captured by the lags model. However, according to [17], they are reflected in the residual correlations. The direction cannot be determined from the data. This phenomenon is known as ‘instantaneous causality’. Within the framework of a forecasting model, instantaneous causality could be interpreted as an indicator for flaws in the model, that is, information which could be used for improving forecasts but is not. On the other hand, if the model is viewed as correct, it is impossible to improve point forecasts by using these correlations which however do affect stochastic forecasting.

IV. BAYESIAN VECTOR AUTOREGRESSION (BVAR)

The Bayesian approach starts with the presumption that the given data set does not contain information in every dimension [12]. This means that by fitting an over parameterized system some coefficients turn out to be non-zero just by pure chance. Since the influence of the corresponding variables is just accidental and does not correspond to a stable relationship inherent in the data, the out-of-sample forecasting performance of such models deteriorates quickly. The role of the Bayesian prior can therefore be described as prohibiting coefficients to be nonzero ‘too easily’ [15]. Only if the data really provide information will the barrier raised by the prior be broken through [13].

The next step consists in the specification of a prior distribution for the coefficients. In this paper the so called ‘Minnesota prior’ is used see [5]. It specifies a random walk process with drift for each of the variables involved and does not allow for influences of own lags beyond the first one and of other variables. This specification does not represent a genuine Bayesian prior, since it does not characterize the beliefs of an investigator, who usually postulates some relationships among those variables. The Minnesota prior could however be regarded as the intersection of the a priori beliefs of many economists. In this sense it represents an improvement over the so called ‘diffuse prior’, which is often used to represent the notion of ‘knowing little’.

Since the prior distribution is specified as a multivariate normal, it is necessary to set, besides the mean, the standard deviations of the coefficient of variable j with lag l in the below equation. And the covariances are set equal to zero. Instead of specifying each standard deviation separately, they are set as a function of 3 ‘meta-parameters ’$\tau, w,$ and d:

$s(i,j,l) = \tau f(i,j) g(l) s_i / s_j$, where

$$f(i,j) = 1.0 \text{ if } i = j$$
$$= w \text{ if } i \neq j, 0 \leq w \leq 1,$$
$$g(l) = d^{l-1}, 0 \leq d \leq 1,$$

And where the scaling factors s_i and s_j adjust for the relative size of the variables. The parameter τ stands for the overall tightness of the prior; a smaller value indicating that more weight is given to the prior. The function $g(l)$ sets the form of the lag pattern, which in this case has corresponding standard deviation. The symmetric function $f(i,j)$ controls the interaction among the different variables; a higher w allows for more interaction by setting a higher a priori standard deviation for cross effects. In this investigation two specifications of the parameters $\tau, w,$ and d are considered:
‘loose prior’ (BVAR-loose): $\tau = 0.2, w = 1.0,$ and $d = 1.0$
‘tight prior’ (BVAR-tight): $\tau = 0.1, w = 0.5,$ and $d = 0.5$

In the first case the lag pattern does not decay and own lags and lags of other variables are treated alike. In the second case the overall tightness is high, the lag pattern decays rapidly, and cross influences are given less weight. The specification also includes four seasonal dummies for each equation. Since no constant term then enters the equations, the coefficients of these variables will determine the drift in the time series. These coefficients are not restricted a priori and are fully determined by the data.

V. FFS Design

In our proposal module, we use the above RVAR and BVAR models in estimating the best faults forecast. The statistics used to evaluate the different forecasts are root mean square error (RMSE), U-statistic of Theil, and mean absolute percentage error (MAPE) [19]. Figure 1 shows flowchart for FFS diagram. First step is to collect the history process variables from the DCS (Distributed Control System). Gathering as much as correct and accurate data is very important as a pre-step before data processing operation. Next step is to arrange the variables and allocate history faults into the history, then divide the history in Time Buckets (TB). It is very important to choose the buckets period not so long, not so short and based on the control system design, complexity of the process, and setup pre-considerations. It could be decided by collaboration with the responsible control engineer. After that, we calculate trend signature for each variable per TB. Trend signature (TS) is considered as stamp for each variable. We use this value per variable per TB in the forecasting operation.

Trend signature is calculated as follows:

1- Apply polynomial regression to each trend
2- Calculate polynomial equation parameters corresponding to each polynomial regression
3- Calculate z-score per each polynomial regression equation which is

$$\frac{\text{Observed value minus the mean value}}{\text{Standard deviation of the values}}$$

So forecasting operation is applied on trend signatures values rather than process variables' original values.

At this stage we became ready to apply forecasting models to the data, and choose the best model using forecasting accuracy measure we mentioned above. Forecast is the future timing of faults, so we can estimate in which TB there will be faults occurrence. We compared the results with actual faults occurrences and proofed that our model is calculating future expectations for faults occurrences accurately and better than usual faults detection techniques, because it is predicting them BEFORE-TIME.

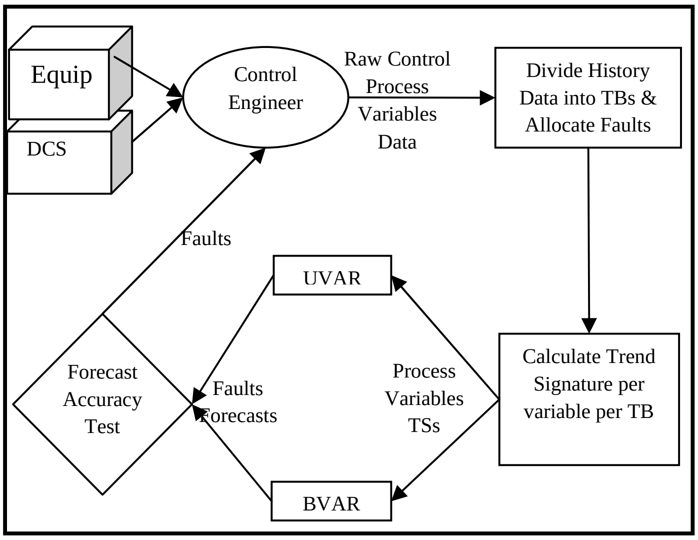

Fig. 1 FFS Model Diagram

FFS advantages over tradition Fault diagnosis systems are:

1) It works offline, so it doesn't take from the run time. That makes it flexibility on time of running, and on the same time it gives faults estimates.
2) It makes forecasting BEFORE-TIME, not ON-TIME, which is supporting the controller and engineer more than current faults detection systems which just gives faults detection ON-TIME.

VI. Experiments & Results

Our experiment is done through chemical plant, which is designed and implemented in Okayama University Laboratory, Japan. The process is established in order to check and test different methodologies for detecting and diagnosing faults. The plant is consisting of tanks, pumps, sensors, alarms, control valves, and manipulated valves. The material used is water and the objecting is to circulate cold and hot water in two different circles and exchange temperatures between them.

Alarms are used to check the process variables limits such as level of water in the tanks. Sensors are used to measure different process variables such as temperature, pressure, and vibration level in different locations in the plant. We used DCS to measure the process variables and keep the history, also as controller for the pumps, and valves. Used process variables are Temperature: TK2, TK3, TC1, and TC2; Pressure: PS1; Level: LS1, LS2, and LS3.

We apply two different forecasting scenarios and several criteria for the goodness of fit over the forecasting intervals. Furthermore, the two approaches are contrasted to an 'unrestricted' VAR model with 6 lags for each variable in each equation (UVAR-6) to demonstrate how over parameterization affects forecasts performance.

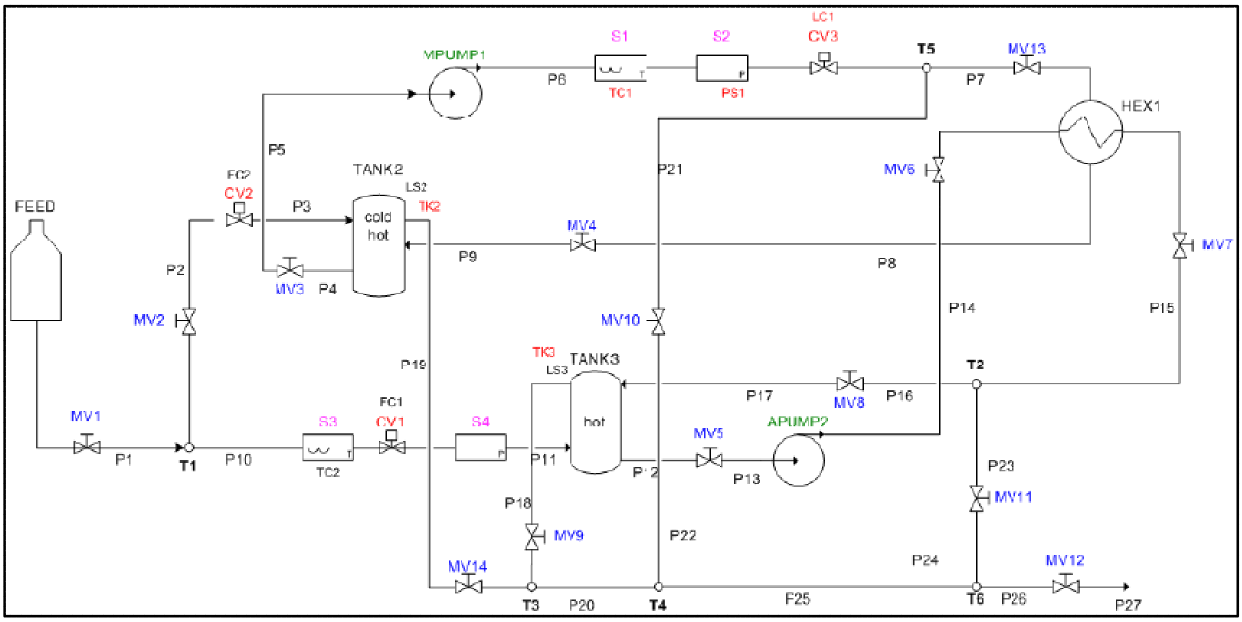

Fig. 2 Experimental Chemical Process Diagram

The first scenario consists of an 'ex-ante' forecast for history of control process monitoring system over 16 history TBs from TB50 to TB65. For this exercise each model is estimated over history before that period by around 30 TB periods from TB20 to TB49, and used to generate forecasts of each variable for the 16 TBs. Then the information of the TB50 is incorporated into the model by updating the parameters through Kalman filtering and a new set of forecasts is generated, now going from TB51 to TB65. This procedure is repeated until TB65 is reached when all the available information is used. In this way 16 one period, 15 two period, 14 three period,…, and 1 sixteen period forecast are generated, which can be checked against the actual realizations. The statistics used to evaluate the different forecasts are RMSE, U-statistic of [6], MAPE. The first two criteria are based on quadratic loss functions. Unfortunately, true forecaster's loss function is unknown. It even may be skew, with different costs for optimistic and pessimistic mistakes see [1]. However, as the modeling procedures rely on quadratic criteria, quadratic loss is a useful technical assumption.

Whereas ex-ante forecasting is methodologically closer to the actual situation of the forecaster who iteratively adapts his model to the data, ex-post forecasting is compatible with asymptotic theory which postulates a true model that is completely identifiable in the long run. The second exercise therefore computes ex-post forecasts over TB50-TB65, where the whole sample period is used for estimation. The statistics in this case are the mean forecast error (the bias), the standard deviation, and the value of the T-statistic against the null hypothesis that the mean forecast error is zero.

The general conclusion to be drawn from the models' ex-ante performance is documented in Tables 1-3 which show a marked superiority of RVAR and BVAR-tight over UVAR-6 and BVAR-loose which is not shown here to save space. Tables' rows are showing the RMSE, Theil's U statistic, and MAPE respectively. For short forecast horizons up to 3 TBs ahead, RVAR almost dominates. For longer horizons, RVAR loses ground relative to BVAR-tight which predicts four of the series better at step 8, but only one at step 1. RVAR and BVAR-loose are the only specifications with all U-statistics for one period ahead smaller than one, however, BVAR-loose quickly deteriorates as the forecast horizon becomes longer. Steps 4 and 8, which reflect the treatment of seasonality, put up severe problems for all models, but BVAR-tight seems to be most robust in this direction.

TABLE I
EX-ANTE FORECASTS FROM THE UVAR-6 MODEL FOR THE PERIOD TB50-TB65

	Forecast Step							
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
TK2	0.012	0.015	0.016	0.188	0.026	0.032	0.039	0.040
	0.133	0.142	0.167	0.967	0.283	0.300	0.375	1.100
	0.183	0.217	0.250	0.308	0.433	0.542	0.650	0.667
TK3	0.003	0.005	0.007	0.009	0.012	0.015	0.018	0.020
	0.150	0.192	0.358	0.925	0.542	0.517	0.750	1.117
	0.025	0.050	0.083	0.108	0.142	0.167	0.217	0.242
TC1	0.017	0.025	0.028	0.030	0.031	0.033	0.033	0.027
	0.650	0.617	0.508	0.433	0.358	0.317	0.267	0.192
	0.283	0.425	0.467	0.467	0.525	0.617	0.617	0.525
TC2	0.010	0.014	0.014	0.018	0.019	0.020	0.017	0.018
	0.375	0.408	0.325	0.333	0.275	0.258	0.200	0.183
	2.383	3.642	3.817	4.333	4.758	5.100	4.217	4.392
PS1	0.256	0.456	0.666	0.808	1.026	1.251	1.451	1.597
	0.625	0.608	0.642	0.642	0.675	0.717	0.742	0.742
	2.292	3.950	63.608	7.908	9.850	11.992	14.758	17.400
LS1	0.026	0.033	0.040	0.043	0.049	0.053	0.059	0.059
	0.575	0.758	0.775	1.467	1.058	1.267	1.100	1.617
	31.675	43.117	51.108	59.592	72.475	79.600	90.750	98.417
LS2	0.010	0.009	0.011	0.013	0.020	0.019	0.026	0.029
	0.117	0.250	0.125	0.242	0.183	0.242	0.208	0.275
	0.217	0.183	0.258	0.292	0.433	0.442	0.600	0.642
LS3	0.032	0.038	0.050	0.058	0.065	0.074	0.079	0.095
	0.525	0.717	0.708	1.025	0.800	0.858	0.800	1.008
	0.633	0.683	0.933	1.142	1.433	1.683	1.833	2.100

The performance of UVAR-6 can be improved by setting all lags of order 5 and 6 to zero. This agrees with the supposed deteriorating influence of insignificant parameters. It is worth to contrast these results with the one obtained by [7] who arrive at exactly the opposite conclusion, that is, an improvement in forecasting with an increasing number of free parameters.

TABLE II
EX-ANTE FORECASTS FROM THE RVAR MODEL FOR THE PERIOD TB50-TB65

	Forecast Step							
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
TK2	0.012	0.015	0.016	0.188	0.026	0.032	0.039	0.040
	0.133	0.142	0.167	0.967	0.283	0.300	0.375	1.100
	0.183	0.217	0.250	0.308	0.433	0.542	0.650	0.667
TK3	0.003	0.005	0.007	0.009	0.012	0.015	0.018	0.020
	0.150	0.192	0.358	0.925	0.542	0.517	0.750	1.117
	0.025	0.050	0.083	0.108	0.142	0.167	0.217	0.242
TC1	0.017	0.025	0.028	0.030	0.031	0.033	0.033	0.027
	0.650	0.617	0.508	0.433	0.358	0.317	0.267	0.192
	0.283	0.425	0.467	0.467	0.525	0.617	0.617	0.525
TC2	0.010	0.014	0.014	0.018	0.019	0.020	0.017	0.018
	0.375	0.408	0.325	0.333	0.275	0.258	0.200	0.183
	2.383	3.642	3.817	4.333	4.758	5.100	4.217	4.392
PS1	0.256	0.456	0.666	0.808	1.026	1.251	1.451	1.597
	0.625	0.608	0.642	0.642	0.675	0.717	0.742	0.742
	2.292	3.950	63.608	7.908	9.850	11.992	14.758	17.400
LS1	0.026	0.033	0.040	0.043	0.049	0.053	0.059	0.059
	0.575	0.758	0.775	1.467	1.058	1.267	1.100	1.617
	31.675	43.117	51.108	59.592	72.475	79.600	90.750	98.417
LS2	0.010	0.009	0.011	0.013	0.020	0.019	0.026	0.029
	0.117	0.250	0.125	0.242	0.183	0.242	0.208	0.275
	0.217	0.183	0.258	0.292	0.433	0.442	0.600	0.642
LS3	0.032	0.038	0.050	0.058	0.065	0.074	0.079	0.095
	0.525	0.717	0.708	1.025	0.800	0.858	0.800	1.008
	0.633	0.683	0.933	1.142	1.433	1.683	1.833	2.100

It is possible to improve upon these forecasts by scanning over different values of the 'metaparameters', $\tau, w,$ and d. Using the log-determinant of the matrix composed by cross products of 8 TBs-ahead ex-ante forecast errors during the period TB50-TB65 as a criterion function. Applying this method to the data at hand, values of d close to one and w close to zero - leaving τ unchanged at 0.1 - have been obtained. This means the optimal data based prior' would be a univariate autoregressive model for each of the variables with no cross effects between variables.

This unsatisfactory result is the consequence of a symmetric $f(i, j)$ matrix which treats each of the eight variables in the system alike and could be remedied by putting a weak economic structure on the prior standard deviations.This is done by dividing the variables into core variables of the system which are thought to be important in explaining all the variables of the system and into the rest which are thought to be of lesser importance. This method results in a considerable improvement in the forecasting performance.

TABLE III
EX-ANTE FORECASTS FROM THE BVAR-TIGHT MODEL FOR THE PERIOD TB50-TB65

	Forecast Step							
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
TK2	0.013	0.020	0.021	0.019	0.027	0.034	0.033	0.027
	0.149	0.193	0.228	0.998	0.289	0.315	0.315	0.753
	0.201	0.315	0.324	0.315	0.411	0.569	0.499	0.481
TK3	0.005	0.007	0.011	0.013	0.018	0.021	0.026	0.028
	0.289	0.254	0.525	1.365	0.796	0.744	1.068	1.584
	0.053	0.079	0.123	0.149	0.210	0.263	0.315	0.350
TC1	0.023	0.033	0.034	0.026	0.035	0.044	0.045	0.033
	0.901	0.831	0.621	0.376	0.411	0.420	0.368	0.236
	0.394	0.543	0.586	0.411	0.604	0.735	0.814	0.525
TC2	0.017	0.021	0.022	0.024	0.031	0.035	0.033	0.032
	0.630	0.621	0.508	0.455	0.455	0.455	0.376	0.333
	4.428	5.478	5.250	6.598	7.499	8.173	7.639	8.260
PS1	0.312	0.585	0.811	0.983	1.204	1.397	1.553	1.690
	0.761	0.779	0.788	0.779	0.796	0.796	0.796	0.788
	2.704	5.329	7.245	9.100	11.533	13.825	16.266	18.926
LS1	0.036	0.038	0.041	0.028	0.039	0.040	0.048	0.040
	0.796	0.875	0.796	0.945	0.849	0.963	0.901	1.076
	50.943	47.863	59.238	44.730	64.146	63.954	83.151	69.974
LS2	0.023	0.031	0.026	0.017	0.029	0.041	0.036	0.023
	0.263	0.858	0.271	0.324	0.271	0.516	0.289	0.228
	0.499	0.744	0.543	0.394	0.665	0.893	0.779	0.464
LS3	0.037	0.033	0.040	0.039	0.049	0.053	0.047	0.060
	0.595	0.621	0.757	0.691	0.604	0.621	0.473	0.641
	0.726	0.648	0.718	0.770	0.954	1.173	1.015	1.313

Table III gives the results from ex-post forecasting and shows severe biases, especially with the 'good' models BVAR-tight and RVAR. It might be concluded that UVAR forecasts provide no information relative to no-change but do not show any systematic tendency towards over- or underestimation. As mentioned before, ex-post forecasting methodologically favors non-Bayesian VAR, so the RVAR biases for all but one of the series are even more surprising. This can, however, be explained by regarding the RVAR estimates as pre-test estimates, whose bias is a well-known fact.

TABLE IV
PROCESS VARIABLES WITH FAULTS DATA SAMPLE

Trend Signatures		TK2	TK3	TC1	TC2	PS1	LS1	LS2	LS3	Faults
Training Period	TB20	2.300	3.500	2.800	2.240	1.792	1.434	1.147	0.918	YES
	TB21	2.500	3.400	2.720	2.176	1.741	1.393	1.114	0.891	NO
	TB22	2.670	3.440	2.752	2.202	1.761	1.409	1.127	0.902	NO
	TB23	2.320	3.430	2.744	2.195	1.756	1.405	1.124	0.899	NO
	TB24	2.770	3.330	2.664	2.131	1.705	1.364	1.091	0.873	YES
	TB25	2.870	3.350	2.680	2.144	1.715	1.372	1.098	0.878	NO
	....	...	...	...	...	...	...	...	...	...
	TB49	2.900	3.500	2.800	2.240	1.792	1.434	1.147	0.918	NO
Test Period	TB50	1.725	2.625	2.100	1.680	1.344	1.075	0.860	0.688	NO
	TB51	1.875	2.550	2.040	1.632	1.306	1.044	0.836	0.668	NO
	TB52	2.003	2.580	2.064	1.651	1.321	1.057	0.845	0.676	YES
	TB53	1.740	2.573	2.058	1.646	1.317	1.054	0.843	0.674	NO
	TB54	2.078	2.498	1.998	1.598	1.279	1.023	0.818	0.655	NO
	...	...	...	...	...	...	...	...	...	...
	TB65	2.175	2.625	2.100	1.680	1.344	1.075	0.860	0.688	NO
Forecasting Period	TB66	2.175	2.625	2.100	1.680	1.344	1.075	0.860	0.688	NO
	TB67	1.294	1.969	1.575	1.260	1.008	0.806	0.645	0.516	YES
	TB68	1.406	1.913	1.530	1.224	0.979	0.783	0.627	0.501	NO
	TB69	1.502	1.935	1.548	1.238	0.991	0.793	0.634	0.507	NO
	TB70	1.305	1.929	1.544	1.235	0.988	0.790	0.632	0.506	NO
	TB71	1.558	1.873	1.499	1.199	0.959	0.767	0.614	0.491	NO
	TB72	2.153	2.513	2.010	1.608	1.286	1.029	0.823	0.659	NO
	TB73	1.631	1.969	1.575	1.260	1.008	0.806	0.645	0.516	YES

After doing that deep analysis and comparisons, the model is ready to adapt and choose the best model for every input. And then the outcome is giving the faults timing for the coming TBs. As shown in Table IV.

VII. CONCLUSION & FUTURE WORK

Faults are considered a costly problem for control systems, especially chemical processes. Due to its complexity, and criticality. This issued the need to research and investigates how to detect faults as accurate and early as possible. Previous research is worked on how to detect faults ON-TIME, but our proposal is how to use forecasting techniques with take advantage of analyzing history process variables to estimate when faults is going to happen in future. We used two methods subset modeling and Bayesian techniques. Our experiment is done on chemical process, designed and implemented specially to investigate control and faults diagnosis issues. The results have demonstrated that the RVAR and BVAR-tight are superior in most aspects to the other model specifications. This evidence suggests that the problems associated with an over parameterized model can be avoided by either reducing the number of parameters through exclusion restrictions or by placing prior restrictions on the parameters in a Bayesian way. Using either of these techniques the forecasting performance can be considerably improved. RVAR dominates BVAR-tight for shorter forecasting horizons but not over longer ones. This research work suggests a new methodology for detecting faults in future, as future work we need to link it with faults intelligent knowledge base to be able to suggest to the operator what actions should be taken to avoid the occurrence of future faults.

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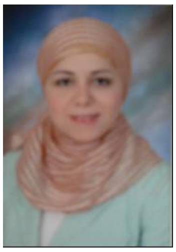

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