THE INTERRELATIONSHIP BETWEEN VIRTUAL ANALYZERS AND ADVANCED TECHNOLOGICAL PROCESS CONTROL SYSTEM

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Abstract: *The implementation of improved technological process control systems (ITCS) represents one of the most effective ways to increase the efficiency of continuous industrial processes. This paper examines the interrelationship between virtual analyzers (VA) and advanced process control systems based on Model Predictive Control (MPC) technology.*

An improved control system is presented as a multi-parameter control architecture for large technological objects that integrates MPC-controllers with a set of virtual analyzers. MPC-controllers enable proactive, multi-variable optimization by solving constrained optimization problems over a short-term prediction horizon using embedded dynamic models of the process. Virtual analyzers, in turn, provide real-time estimation of critical product quality indicators that are difficult or expensive to measure directly, using statistically or physically based models.

Keywords: *Improved control system for technological processes, virtual analyzer, dynamic model, adjustable values, predictive model control system.*

One of the most successful and profitable ways to increase the efficiency of continuous technological processes is the implementation of improved technological process control systems (ITCS).

An improved process control system is understood as a multi-parameter control system for large technological objects (TO) based on a set of virtual analyzers (VA). This system allows for direct quality control of output products in automatic mode. TSO is implemented in the form of specialized software. It interacts with the automated process control system (APS), is specifically configured and configured in accordance with the requirements of a specific process (Fig. 1).

One of the most successful and profitable ways to increase the efficiency of continuous technological processes is the implementation of improved technological process control systems (ITCS).

Virtual analyzers are a valuable tool used in various industrial sectors, including oil refineries, chemical plants, power plants, the pulp and paper and food industries, and nuclear power plants. They are used to solve various tasks, such as backup of measurement systems, “what if” analysis, real-time forecasting for technological device control, sensor inspection, and fault diagnosis strategy.

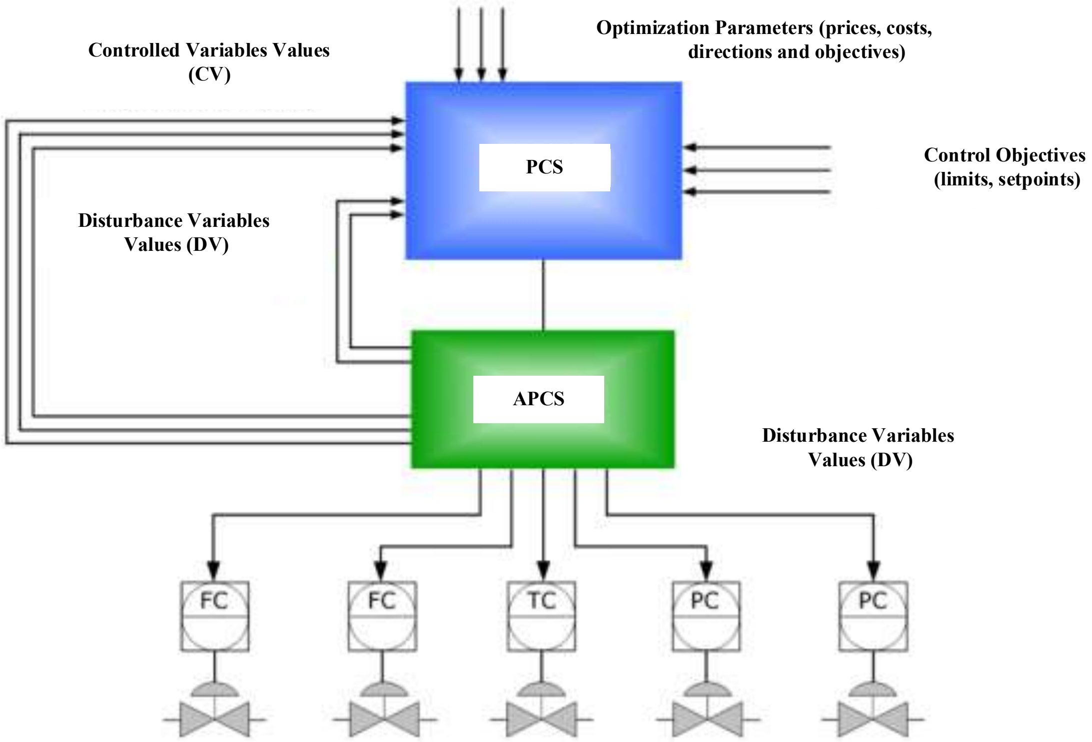

Figure 1. Flowchart of the interaction between TITR and TITR.

As shown in Figure 1, the operating principle of the TPS is based on two main technologies:

- MPC-controllers;
- virtual analyzers.

MPC-controllers implement multi-parameter control of the technological process (TP) by solving optimization problems during the short-term forecasting period using dynamic TP models embedded in them. The constraints of the objective function of an optimization problem usually include difficult-to-measure parameters that characterize the quality of the products being obtained. Virtual analyzers calculate product quality indicators in real-time based on statistically or physically substantiated TJ models.

The management strategy based on the predictive control model (Model Predictive Control MPC) consists of accounting for the future behavior of the object, which allows for an increase in the quality of regulation under conditions of control effects and constraints on controlled technological variables.

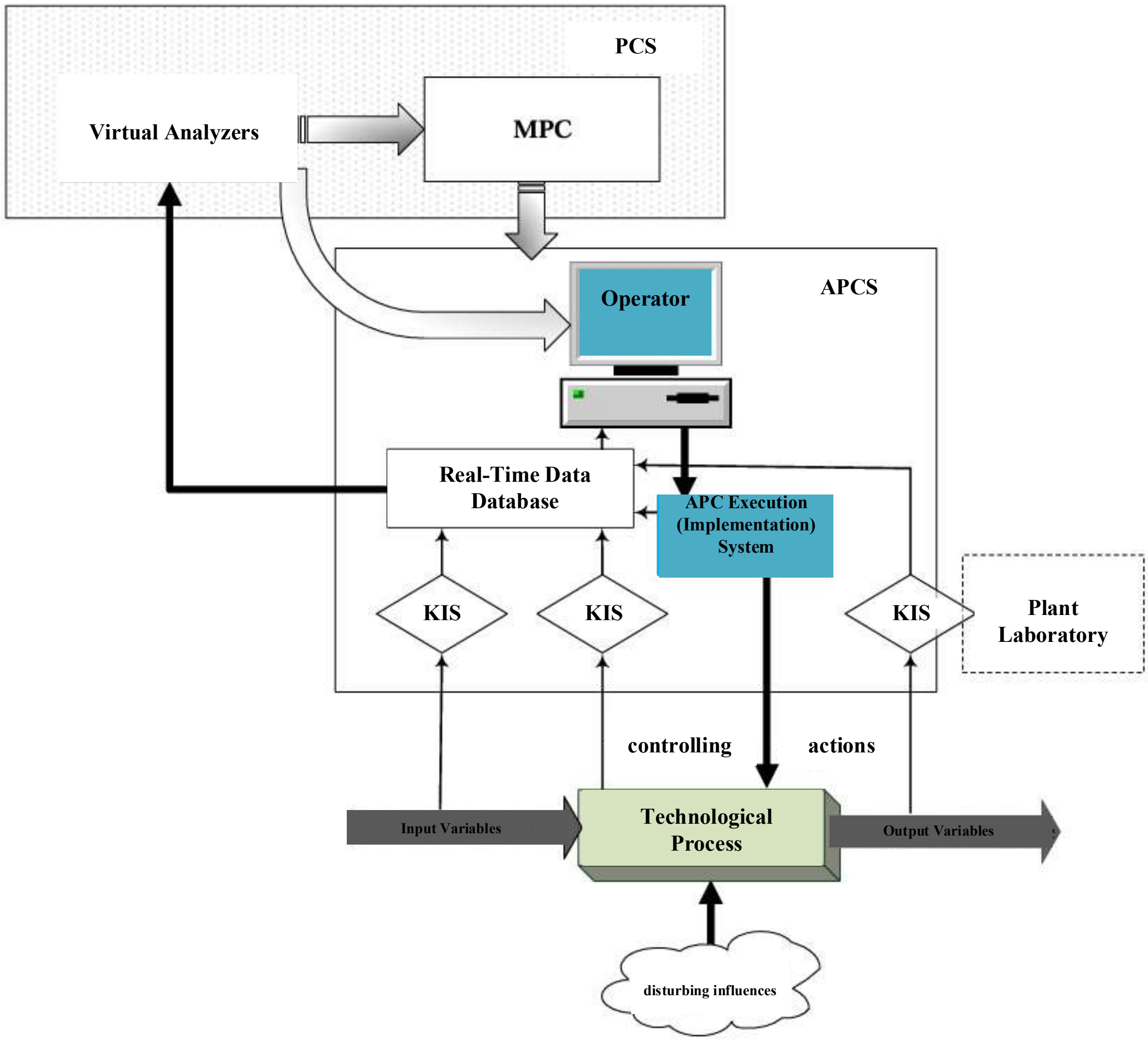

Figure 2. Interaction diagram of TP, TP ABT, and VA in the TP ABT.

The advantages of the TITF operation are as follows:

1. The MPC controller registers perturbation signals and pre-generates control effects.

2. The MPC controller performs multi-parameter control of the TP, taking into account the interaction of parameters.

3. The use of virtual analyzers allows for the implementation of control chains based on product quality indicators.

4. The MPC controller performs uniform control of the subordinate control circuits and maintains the values of the mode parameters close to the permissible limits, thereby reducing the quality reserve of the device's products.

The management strategy based on the predictive control model (Model Predictive Control MPC) consists of accounting for the future behavior of the object, which allows for an increase in the quality of regulation under conditions of control effects and constraints on controlled technological variables. Variables typically controlled by operators are used as manipulable variables (MV), such as the flow rate of the furnace, fuel gas pressure into the furnace, and the rotation speed of the compressor turbine. Controlled variables (CV) are dependent parameters of the technological process, i.e., variables that depend on the MI. These include: 1) they are included in the optimization task, for example, the temperature of the upper part of the column, the position of the control valve, and the pressure drop along the column; 2) product specifications, such as the boiling point of kerosene and the fluidity of polyethylene melt. The composition and temperature of the raw material can serve as perturbed variables (DV), i.e., measurable variables that are not regulated during the control process but influence the values of the regulated variables. The diagram of the predictive model control system is shown in Figure 3.

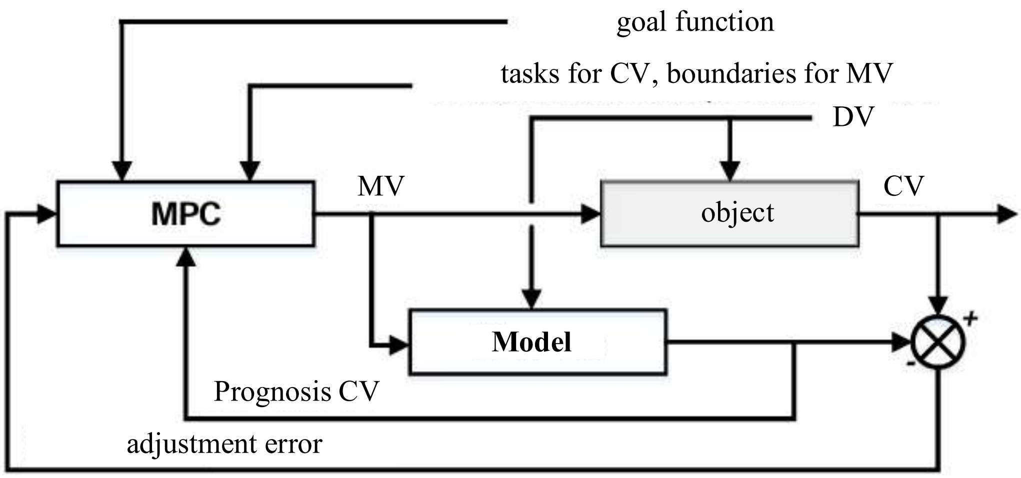

Figure 3. Schematic diagram of the predictive model management system.

The prediction of CV's future behavior is constructed using controlled variables S as a function of future values of MV and measured DV, which relate to the object's manipulated MV and triggered DV models. Future MV values are selected to achieve the optimal value of the criterion while adhering to the constraints in CV and MV. The criterion can be the minimum cost or energy consumption achieved within the range of predicting the object's behavior, maximum performance, etc. To construct a dynamic model, a step-by-step test of the device is conducted, where the MV is subjected to variable actions of a step-by-step nature, and the DV and corresponding CV responses are measured. The data obtained during the tests are processed and the parameters of the models are determined.

To predict the behavior of adjustable variables, a complete process model is used, consisting of a matrix of dynamic submodels, each of which describes the influence of one of the control variables of the MV or the disturbance of the DV on one of the adjustable variables of the SV. The submodel describes how the influence of an independent variable on a regulated variable changes over time, i.e., it reflects a dynamic response. If the independent variable does not affect the adjustable variable, then the submodel is equal to zero. To obtain the models, it is necessary to: 1) obtain dynamic responses of all controlled variables for each control action and each disturbance, and 2) conduct the identification process. Before testing the object, it is necessary to determine how and how strongly the change in the controlled variables occurs when the controlling and perturbing variables change, i.e., the parameter action matrix. The optimization problem solved in the MRS takes the form:

$$\min_{x,y} \|W(Ax-y)\|^2 + x^T \Lambda x_1$$

$$\min_{x,y} \left\| \begin{pmatrix} W & 0 & 0 \\ 0 & W_p & 0 \\ 0 & 0 & W_0 \end{pmatrix} \left(\begin{bmatrix} A \\ A_p \\ S_1 \end{bmatrix} x - \begin{bmatrix} y \\ y_p \\ x_{ss} \end{bmatrix} \right) \right\|^2 + x^T \Lambda x_1,$$

$$y_{lo} \le y \le y_{hi},$$

$$y_{plo} \le y_p \le y_{phi},$$

$$x_{lo} \le x \le x_{hi},$$

$$mv_{lo} \le Sx \le mv_{hi},$$

$$S = \begin{bmatrix} 1 & & & & & & & & 0 \\ \vdots & \ddots & & & & & & & \\ 1 & \dots & 1 & & & & & & \\ & & & 1 & & & & & \\ & \vdots & & \vdots & \ddots & & & & \\ & & & 1 & \dots & 1 & & & \\ & & & & & & 1 & & \\ 0 & & & & & & \vdots & \ddots & \\ & & & & & & 1 & \dots & 1 \end{bmatrix}$$

$$S_1 = \begin{bmatrix} 1 & \dots & 1 & & & & & & \\ & & & 1 & \dots & 1 & & & \\ & & & & & & 1 & \dots & 1 \end{bmatrix},$$

where A is the dynamic matrix of the model (reaction to the unit jump), W is the diagonal weight matrix, S is the sum-sum matrix, $S_1$is the summation matrix, y_{lo}, y_{hi} are the upper and lower boundaries, y_{plo}, $y_{phi}$are the upper and lower boundaries for the formation of manipulable control, x_{lo}, x_{hi} are the upper and lower boundaries of the array of control action increments, mv_{lo}, mv_{hi} are the upper and lower boundaries of the MV, and $x^T \Lambda x_1$ is the penalty variable.

For continuous processes of the chemical-technological type, Honeywell uses robust multi-circuit control technology based on predictive models (Robust Multivariable Predictive Control Technology RMPCT) or Profit Controller. The Profit® Controller module is used in ARS systems in combination with traditional advanced control methods.

The optimization criterion for the Profit® Controller MRS regulator, developed by Honeywell Corporation, is described as follows [6].

$$I = \sum_{j=1}^{\infty} \left(\left\| CV_j - CV_0 \right\|_Q^2 + \left\| MV_j - MV_0 \right\|_R^2 \right)$$

where CV_0 and CV_0 are the specified values of the adjustable variables and the corresponding values of the steady-state control variables, CV_j; and MV_j; are the expected values of the adjustable and control variables, $\|x\|_Q^2 = x^T$ Qx is the norm, and Q and R are the weight coefficient matrices.

Optimization of the management process can also be carried out according to a technical and economic criterion:

$$J = \Sigma_i b_i \cdot CV_i + \Sigma_i a^2{}_i \cdot (CV_i - CV_{0i})^2 + \Sigma_j b_j \cdot CV_j + \Sigma_j a^2{}_j \cdot \left(MV_j - MV_{0j}\right)^2$$

where b_i and a_i are linear and quadratic coefficients for CV_j, and , CV_j are linear and quadratic coefficients for MV_j.

Figure 1.4 shows a comparative analysis of the quality stabilization of methyl-tertiary-butyl ether (MTBE).

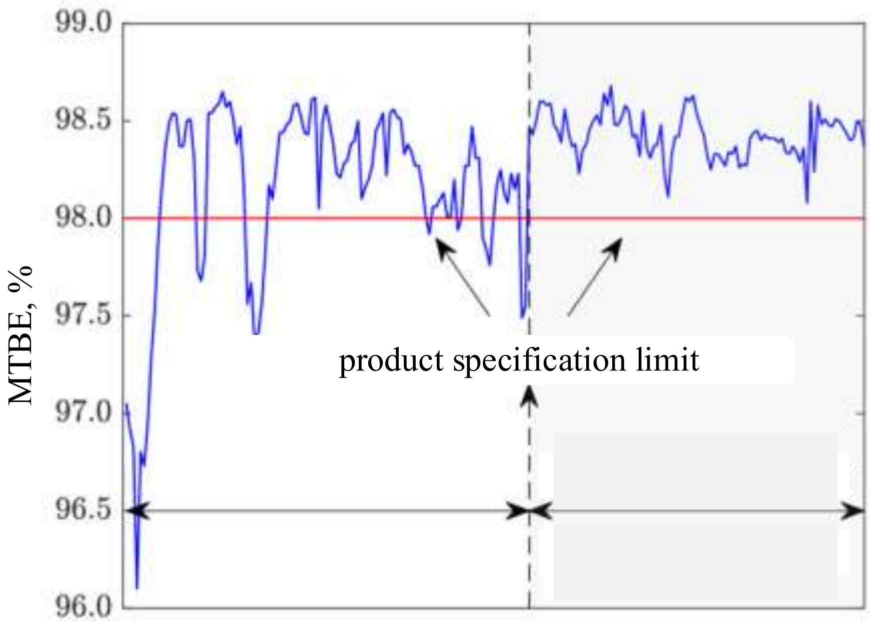

Figure 1.4. Comparative analysis of MUBE quality stabilization before and after the implementation of the TITF.

The main problem in the synthesis of the SES using classical methods of optimal control theory is the high dimensional nature of the SES dynamics models. In this regard, one of the main trends in the development of ESIA is the dissemination of more advanced technologies for the development and support of virtual analyzers using modern achievements in applied statistics, robust control, etc.

Virtual analyzers for monitoring and controlling technological processes

All aspects of developing a virtual analyzer are examined both theoretically and using numerical examples used to highlight the approach being applied, presenting a range of possible approaches. The industry faces the choice of appropriate production policies every day as a result of trade-offs between various constraints. The price and quality of the final product are two important and competitive factors that can determine the industry's success or failure in the market. These aspects are closely related to topics such as electricity and raw material consumption, especially the constant rise in crude oil prices. Companies must comply with laws that impose increasingly stringent limits on the technical specifications of products and the emissions of pollutants by industrial enterprises. Such restrictions create difficulties for technologists and operators, requiring the proper execution of technological processes, including in emergency situations. This process is only possible if you have a deep understanding of the process that corresponds to it.

Therefore, it is clear that it is important to monitor a large set of process variables by installing and using adequate measurement systems (usually in the form of distributed monitoring networks). Unfortunately, measuring devices usually have to operate in an unfavorable environment, which, on the one hand, requires the instruments to meet very strict design standards, and on the other hand, requires a maintenance protocol. In any case, it is impossible to completely avoid the occurrence of unexpected malfunctions. Nevertheless, some measurement tools can introduce significant delays into the operation of systems, which can reduce management efficiency. The installation and maintenance of measuring instruments designed for monitoring a large enterprise is never cheap, and the required budget can have a significant impact on the overall operational costs of the enterprise, which is usually aimed at reducing the total number of controlled variables and/or the frequency of observations, although in many industrial situations, rare sampling of certain process variables (lack of PA flow analyzers) can cause potential operational problems. Variables related to product quality are commonly detected in standalone mode using laboratory analyses, which causes disruptions and significant delays.

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