A Computer Based Tool for the Simulation, Integrated Design and Advanced Control of Wastewater Treatment Processes
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A Computer Based Tool for the Simulation, Integrated Design and Advanced Control of Wastewater Treatment Processes

P. Vega,[a] F. Alawneh,[b] L. Gonzalez,[b] M. Francisco [a], B Perez [b]

[a] University of Salamanca, Dept. Informática y Automatica, Escuela Tecnica Superior de Ingeniería Industrial, c/ Fernando Ballesteros s/n, 37700 Bejar (Salamanca), Spain

[b] *Universidad de Salamanca, Dept. Informatica y Automatica, Facultad de Ciencias, c/ Plaza de la Merced s/n, 37008 Salamanca, Spain*

Abstract

The objective of this work is the development of a Computer Based Tool for the Simulation, Integrated Design of Activated Sludge Processes and their Control Systems. Integrated Design methodology allows for the simultaneous design and evaluation of plants and control system parameters. In the paper, the ID problem is stated mathematically as a constrained non-linear multi-objective optimization problem, in which economic and control objectives are considered together with some constraints. The solution of the problem is obtained following a numerical cost optimization procedure that uses dynamic models together with a set of predefined constraints to evaluate plant dimensions, operation points and controller parameters. The constraints are selected to ensure that the process variables and some controllability measures lie within specified bounds. In this context, the aim of the work was to design and to implement a software tools to support engineers during the complex task of designing Wastewater Treatment Plants. The integration of Numerical Optimization, Model Identification, Dynamical Model Simulation and Model Based Predictive Control, is the most relevant feature of the package and the key point to succeed in the design of flexible processes reducing the operation costs while legal specifications on the quality of the treated water are fulfilled. The package allows dealing with different type of treatment processes, several plant configurations and scenarios. Some of the available models and data records, representing real Wastewater Treatment Plants, can be taken as starting point either for being redesigned or just as simulation models (to be compared with others, for its control system design, etc.). In fact, the software is very flexible and, apart from the first main functionality (Integrated Design), the use of other implemented modules can lead to the integration of various related fields (Simulation, Control System Design, Fault Detection and Diagnosis, Adaptive Control, etc).
The paper begins with a simple introduction to the Integrated Design concept, problem definition, and support tool design, to end up with some application examples.

Keywords: Process and Control Integrated Design, Advanced Control, Multi- Objective Optimisation, System Identification.

1. Introduction

The public view concerning wastewater treatment these days is fairly positive. The EU Urban Water Directive (91/271/EC) adopted years ago, together with the newly adopted EU Water Framework Directive (2000/60/EC), define stringent requirements for urban wastewater treatment and a time frame for the step-wise implementation by the member countries. The application of the directive has lead to the construction of new plants and redesigns of the existing plants with the aim of reducing as much as possible the level of pollutant and the environmental impact.
This norm imposes several objectives to achieve, like the design of more complex and flexible plants considering the new environmental restrictions facilitating their adaptation to future environmental legislations, and avoiding their redesign, and for the urgent need to realize a stricter Operation and Control (more quality of the water, menus sludge production...). To achieve the above mentioned objectives, its necessary the use of Integrated Design Techniques of the plants and their control systems, Advanced Control Techniques and Intelligent Supervision, and the use of a Computer Aided Tools that permit the simulation and design of plants and controllers.
Traditionally, process design and control system design are performed sequentially. It is only recently displayed that a simultaneous approach to the design and control leads to significant economic benefits and improved dynamic performance during plant operation.
The field of integrated process design and control has reached a maturity level that mingles the best from process knowledge and understanding control theory on one side, with the best from numerical analysis and optimisation on the other. Direct implementation of integrated methods should soon become the mainstream design procedure. (Seferlis, Georgiadis, 2004).
Within this context, 'The Integration of Process Design and Control' brings together the development of a variety of design tools for the process design which has immense potential because of its several advantages. The biggest is that it will reduce costs significantly. It will also reduce the iterations between separate design operations - like synthesis and control system design, in addition to save design time, and improve design efficiency.
Moving beyond the present, there are other reasons also as to why it's strongly advocate and feel that the time has come for integrated tool suites. Today's designers need to consider several critical parameters and objectives. All of these parameters are closely coupled - optimisation of one affects the others. Their interrelationships require design tools that can perform concurrent optimisation, which can only be accomplished when the tools are part of an integrated design-tool suite and used within the right design flow. Concurrent optimisation lets the designer solve problems that affect multiple design parameters.
Jussi, et al 2005 presented an integrated multi-objective design tool for chemical process design that combines the rigorous calculation of the BALAS process simulator and the interactive multi-objective optimisation method NIMBUS. Pajula, Ritala, 2006 presented a tool for the uncertainty measurement in the integrated control and process design showing a study how the control structure design is affected by uncertainty measurement and how the corresponding dynamic problem is defined and

solved with rather regular tools. Choo et al, 2004 proposed DePlan as a method for integrated design management during the detail design phase; DePlan integrates two techniques, namely, Analytical Design Planning Technique and planning according to Last Planner, each involving a software tool.
Lim et al. 1999 applied a multi-objective optimisation concept to chemical processes. They used sequential modular simulator ProSim and an optimiser based on infeasible path successive quadratic programming (SQP). Two objectives were analysed, namely a global pollution index functions and the cost-benefit functions.
In this tool designing and implementation phase, we tried to integrated various optimisation algorithm and the sate of the arte advanced control system that show high efficiency in the waste water control process. Many simulation software packages such as ASPEN PLUS, CHEMCAD and BALAS include single objective optimisation capabilities. These optimisation tools can be used for simple multi-objective optimisation; however, these simple tools are not efficient in solving complex real world process, Miettinen, 1999. With our integrated tool the designer can consider several conflicting performance criteria simultaneously and find efficient design alternatives in flexible way.
The main contributions of the method used in this work are the following. First, a new method for optimal automatic tuning of linear MPC controller parameters taking into account input and output constraints, and making use of a specific random search method based on the optimisation algorithm (Solis, 1981) for MPC integer parameters tuning, has been developed and tried for linear plants and the activated sludge process. The second contribution is to develop integrated design techniques in order to perform at the same time the design of the optimal plant for activated sludge process and the optimal linear MPC for this process. This strategy has been tested in one simulated example based on a real wastewater treatment plant. In addition to costs, other performance specifications were considered in the integrated design procedure, such as the Integral Square Error (ISE) or the integral of changes in the manipulated variables. The methodology proposed here is a general one, and any other dynamical performance criteria can be considered. The use of linear models also allows us for the specification of other convex performance criteria using an LMI framework.

2. Integrated Design

Integrated Design methodology considers that the changes in the process design might make the system more controllable. The methodology allows for the evaluation of the plant parameters and the control system at the same time. The problem is stated mathematically as a non-linear multi-objective optimisation problem with non-linear constraints, including economic and control considerations.
The methodology that the support tool use combines the design of the plant, and the controller following a cost optimisation procedure, with the desired closed loop dynamic as constraints. The cost functions include the investment, operation costs, and dynamical indexes (like the Integral Square Error (ISE)). The constraints are selected to ensure that the values of some controllability parameters, the $H\infty$ norm performance and many other performance criteria are within specified bounds. The independent variable set includes plant dimensions, an operation point and the

controller parameter. This problem is stated mathematically as a NLP /DAE multi-objective optimisation problem with non-linear constraints. Many works apply integrated design techniques, particularly to chemical process design (distillation systems, reactors, etc.), stressing the interactions of design and control (Ross, 2001; Gil, 2001). These works also tackle process structure selection by solving a synthesis problem. A comprehensive review of advances in the area is given in (Sakizlis, 2004). Some good examples of integrated design applied to the activated sludge process are (Francisco, 2003), where PI controllers and the plant were obtained, including linear matrix inequality (LMI) constraints to state stability conditions and some desired closed-loop behaviour, and (Vega, 1999), that presents an study of integrated design with PI controllers applied to different plant structures. Despite of the complicated dynamics of the process under design, works adding advanced controllers to the integrated design procedure have not been reported in the literature, and it could be a good way to improve control performance. In this work we have selected advanced controller because of the existence of several successful applications in activated sludge control (Vega, 1999; Nejjari, 1999; Sotomayor, 2002), and the easiness to deal with constraints.

Mathematically the Integrated Design can be formulated as:

$$\min_x \; f(x)$$

Subject to $lb \le x \le ub$

$g(x) \le 0$

Where x = plant dimensions, flows and working point parameters.
lb = lower bounds for optimisation variables.
ub = upper bounds for optimisation variables.
g = non-linear function that represents the physical, process and controllability constraints.
g(x) is the mathematical model of the optimisation problem

The problem as we mentioned before can be classified as a non-linear multi-objective optimization problem, that consists of several conflicting objective functions describing the properties that we want to improve and constrains that determine a feasible solution. The cost function could include three cost elements, which are, construction cost, operational cost, and controllability. The feasible solution is a set of design parameters which optimise the cost function subject to group of constrains which include the physical, operational, and controllability constrains.

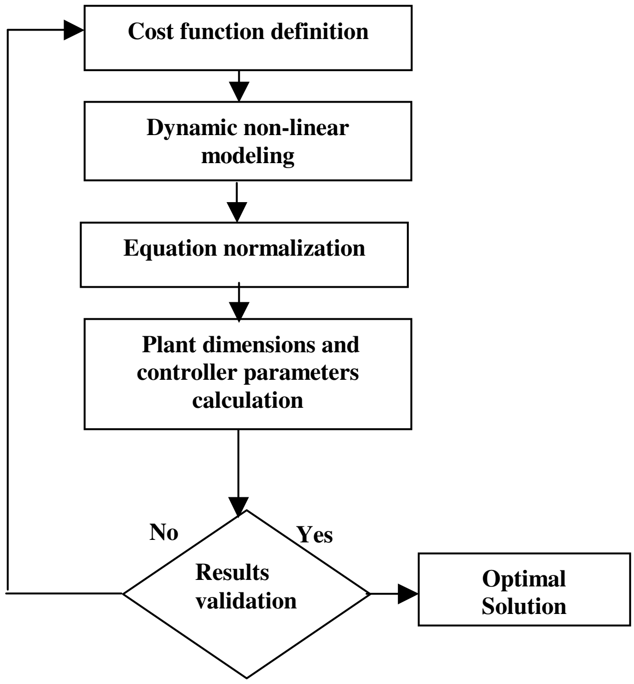

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Figure. 2.1 Integrated Design Methodology

Mathematical Optimization for Integrated Design

The discussion of this section assumes that the objective function of the optimization problem is to be minimized (rather than maximized), unless stated otherwise.
The objective of the application of an optimization procedure is to find values of the parameters describing the plant dimension, and to find values of the parameters describing the control strategy so that minimum possible adverse impacts of the strategy are applied to the environment. Solutions resulting not only in minimum impacts but also those leading to less detrimental impacts than the currently applied strategies minimizing a cost functions.
The control strategy is applied during the simulation, the tool serves as a means of the computing the objective function within the optimization procedure. The tool has the strategy parameters as input (controller type, control parameters, identification parameters, initial values, process restrictions…etc) and the value of objective function, plant dimension, and control strategy parameters as output. See Figure 2.2

Advanced Control for Integrated Design

The allowed levels of pollutants in treated wastewater have become increasingly stringent with time. Taking into account current environmental problems, it is not unrealistic to believe that this trend will continue. At the same time loads on existing plants are expected to increase due to growth of urban areas. This situation demands more efficient treatment procedures for wastewater.

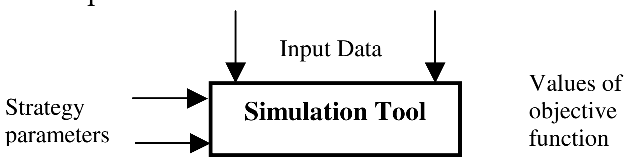

Figure 2.2 Role of the simulation tools in the definition of the optimization problem

One way to improve efficiency could be to construct new and larger basins, but this is expensive and often impossible since the land required is just not available. Another way would be the introduction of more advanced control and operating systems. This is expected to reduce
the need for larger volumes, improve the effluent water quality, decrease the use of chemicals, and save energy and operational costs. Sustainable solutions to the problems of wastewater treatment will require the development of adequate control systems.

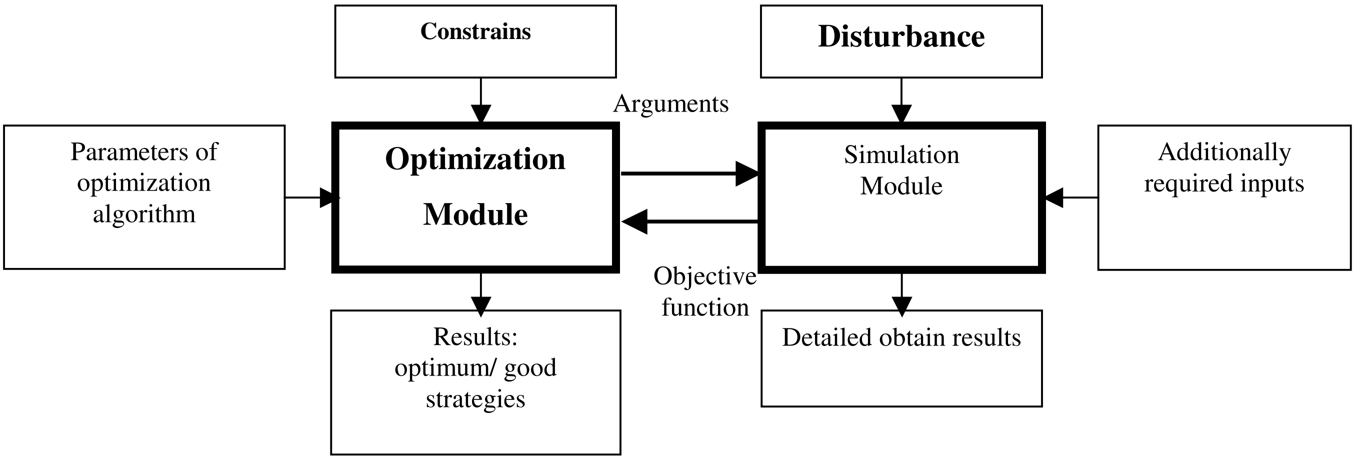

Figure 2.3 Iterative loop for integrated design

New control strategies may involve the use of simplified biological/physical models, feed forward control from measurable disturbances, simple estimation models, supervision control, and real-time estimation. For a control engineer the activated sludge process in a wastewater treatment plant is a challenging topic for several reasons like that the process is time-varying, non-linear, and multi-variable. From the nature of wastewater treatment process it can be shown that a simple control loops is not sufficient and it was one of the motivations beside the cost effective to the use of advanced control strategies.
One important issue in integrated design is the tuning of controller parameters. Usually the tuning of these parameters has been performed using expert knowledge and a trial and error procedure. However some works deal with automatic tuning of MPC controllers. (Ali, 1993) proposed a procedure for tuning the algorithm parameters of a non-linear predictive controller. This was accomplished by using an off-line interactive multi-objective optimization package, specifying time-domain performance criteria. Results are good, but the tuning of integer parameters such as horizons is performed using a non intelligent grid search. For linear model predictive control, (Al-Ghazzawi, 2001) has developed an on-line tuning strategy based on the linear approximation between the closed-loop predicted output and the MPC tuning parameters, but without considering output constraints on the on-line optimization step.

When tackling the integrated design mathematical problem, specific features of the process (non-linearity, different sensitivity for plant parameters and controller parameters, etc.) increase the complexity of the problem. For this reason, when solving closed loop integrated design, we used a methodology consisting of an iterative two steps approach. For open loop design, optimization of function (1) is sufficient, but for closed loop integrated design, the optimization procedure involves the two cost functions (1) and f2. The first step performs the plant design optimizing f1, and the second step the controller tuning optimizing f2. At every step, plant or controller parameters obtained are used as constant values for the following optimization step. The loop ends when a convergence criterion is reached. (Figure 2.4).

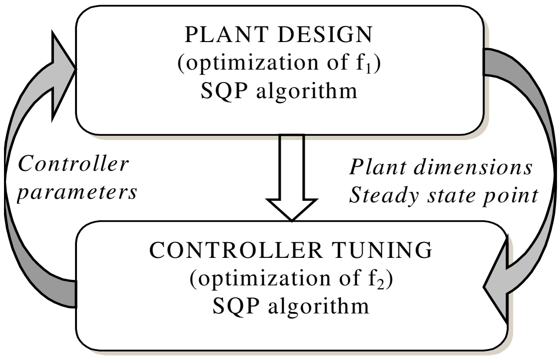

Figure. 2.4 Iterative loop for integrated design

3. The Computer Based Tool

This tool has been developed as a prototype tool for the Simulation, Integrated Design, and Control System Design Process for activated sludge process, beside the Integrated Design module, the tool contains a simulation module that able the user to simulate the most common fault occurs in the waste water treatment plants, and a Control System Design Module for the design of Wastewater Plants control loops. Figure 3.1 shows the general schema of the Integrated Design Module.
The tool contains considerable number of user case like Plant Design, Integrated Design (Plants + controller), various types of controller (PID, MPC....etc),different optimization algorithm, various cost function formulate simulation with/without faults, control system design (PID, MBPC, GMV…etc).
The package is an integrated tool for optimization system which integrates programs for the optimization and predictive control of WWTP (Activated Sludge Processes), simulators (SIMULINK), computer aided control system design (Matlab, toolboxes) and user interface (GUIDE toolbox).

Integrated Design Module Main Component

Three types of elements can be distinguished in the tool: section of parameters, menus, and graphics. The first one is composed by the different parameters that define the problem to optimise, optimisation methods, disturbances, set of constrains, simulation parameters and type for both the model and the plant. On these parameters it is possible to interactively modify a lot of parameters like optimization parameter, constraints, simulation parameters, disturbance etc. The second set of elements mainly allows modifying the initial values, load optimise plants, and save the obtained results. set of elements is linked to the menu file from which it is possible to modify the initial vales for the plant and save obtained results, third elements usually use to show the obtained results graphically, system behaviour via simulation, and to compare the obtained results of different plant configuration.

1. Plant type: (without/with N Removal) at the first the visual appearance of the wastewater was improved via sedimentation and filtration process. The visual problems were of course the most obvious, and also the most simple to deal with. To improve the situation, biological treatment is evolved. This treatment consisted of adding oxygen to wastewater in reactor, thus allowing the organic matter to oxidize (Plants without Nitrogen Removal), the objectives of these plants was the elimination of organic matter from the wastewater and keep its concentration below a certain limits, In the 1980s, nutrient pollution from nitrogen and phosphorus was found to cause problems such as eutrophication, and the focus therefore shifted towards removal of nutrients from wastewater. (Plants with Nitrogen Removal, to remove organic matter and nutrients. In 1990s the EU Urban Water Directive (91/271/EC) increasing the demands on nitrogen removal from wastewater in the member country (Samuelson, 2005).
2. Cost Function: The Integrated Design, for the activated sludge process, consists of minimizing an objective function which represents construction, and operation costs,(Controllability can be also consider as a part of the objective function) while the desired open or closed loop dynamic is considered as constraint. Mathematically it is stated as a NLP/DAE optimization of the cost function, subject to process and controllability constraints. The tool considers three formulas for the cost function definition, the first formula contains the construction and operational cost, the second considers the controllability but as part of the original cost function, the third formula considers the controllability but as separate function.
3. Optimization Algorithm: The tool combines between the classical gradient based optimization techniques such as sequential quadratic programming (SQP) and the stochastic optimisation techniques such as genetic algorithms and simulated annealing. The classical gradient based optimization techniques,, have being broadly applied for constrained optimisation obtaining good solutions in a reasonable amount of computing time (Edgar, 2001; Gill, 1981). However, for complex problems these algorithms sometimes fail to give any solution, and its effectiveness decreases when discontinuities and non convexity are present. The tool uses a two steps optimization approach that has been developed by Salamanca University to improve SQP algorithm convergence and results.

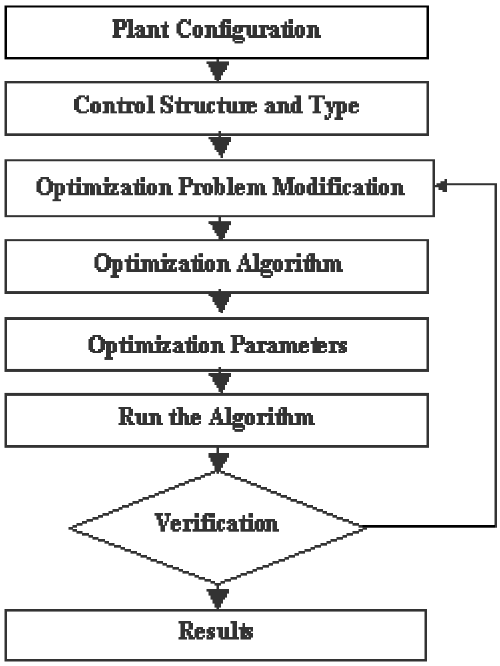

Figure 3.1 General Scheme of the Integrated Design Module.

The stochastic optimisation techniques such as genetic algorithms and simulated annealing (Salamon, 2002; Laarhoven, 1987) are recommended for complex non-linear and discontinuous problems where classical optimisation techniques might fail. This algorithms have been used with good results for this type of problems, and particularly for solving process synthesis (Costa and Oliveira, 2001; Tsai and Chang, 2001; Revollar et al., 2004), but their main drawback is the difficulty to handle constrained problems because the stochastic search operators frequently produce infeasible solutions.
Also the tool use a hybrid method for the solution of these complex problems, such as process integrated design and synthesis, combining genetic algorithms and SQP to make use of the advantages of both methods. First, the genetic algorithm is good to find candidate solutions close to an optimum, exploring all the search space, without suffering numerical problems, and then these candidate solutions are improved using SQP methods to find a real feasible optimum. Figure 3.1
In the integrated design problem, the iteration between control and process design is avoided because the dynamic analysis is included in the simultaneous control and design optimization. However, this means that external disturbances and changes of operation point become a part of the problem formulation. Defining realistic scenarios for disturbances and changes in operation point, and, in particular, their frequency of occurrence is a most challenging task. The knowledge gained from earlier experiences with the same or similar processes is highly valuable in design. (In the tool we use two type of disturbance, real disturbance taking from Manresa Plant, Spain, and Cost 624 Benchmark disturbance). The co-existence of disturbances and

their frequencies need to be carefully studied in order to include all relevant process specific interactions in the scenarios. Whenever disturbances are measurable, the design superstructure should include these measurements and the control structure based on the measurements. The disturbances during transients, such as changes of operation point are often known to differ from those in stationary operation. The design superstructure should allow controllers to be tuned differently in these cases. Obviously, this results in a search space of increased complexity. The scenario data greatly affects the optimization results.

4. Restrictions: Physical, Operational, and Controllability Constrains. The controllability constraints are stated to guarantee disturbance rejection capability, either in open or closed loop status. Example of controllability constrains are:

$$ISE = \int_{t=0}^{T\max} (s_{1_r} - s_1)^2 \cdot dt$$

Where T_{max} =165 hours is the simulation time and (s_{1r}) is the steady-state value or reference for substrate.

5. Controllers: The most common control strategies for the activated sludge control process are used in the tool.

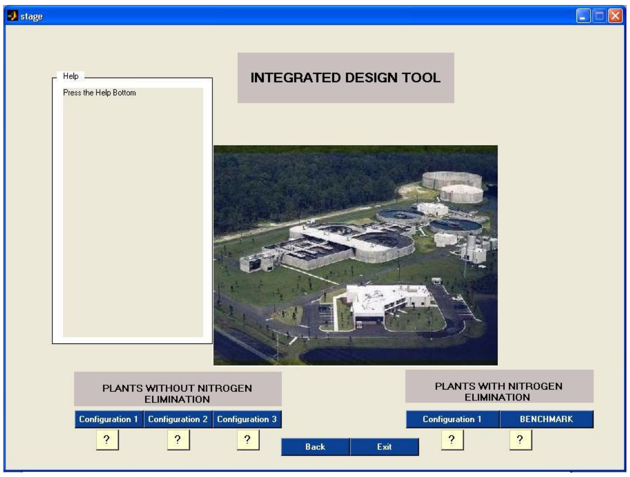

Figure 3.2 Plant Selection Interface.

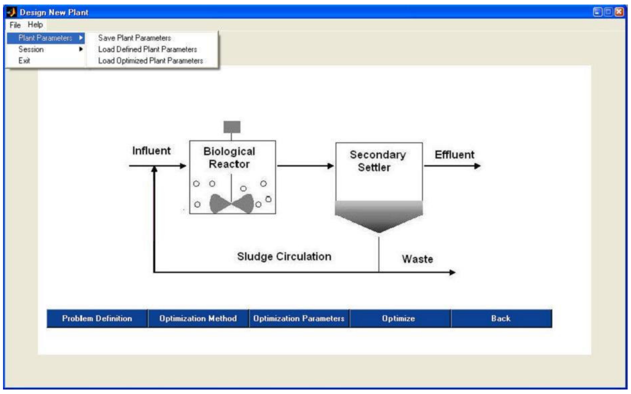

Figure 3.3 Integrated Design Module Interface.

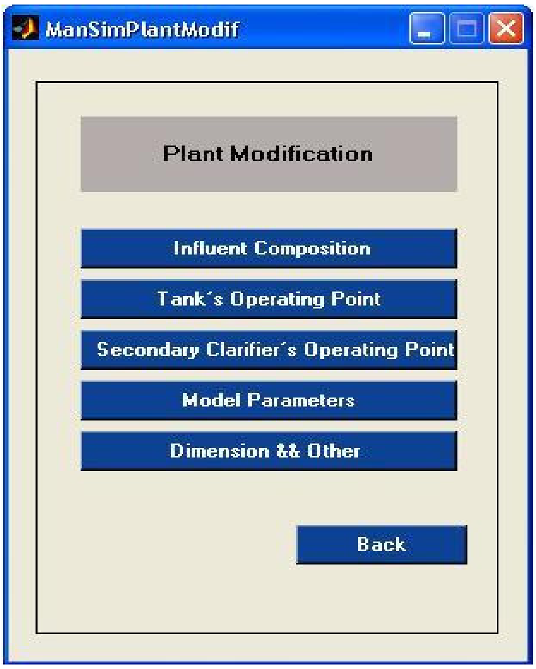

Figure 3.4 Plant Modification Interface.

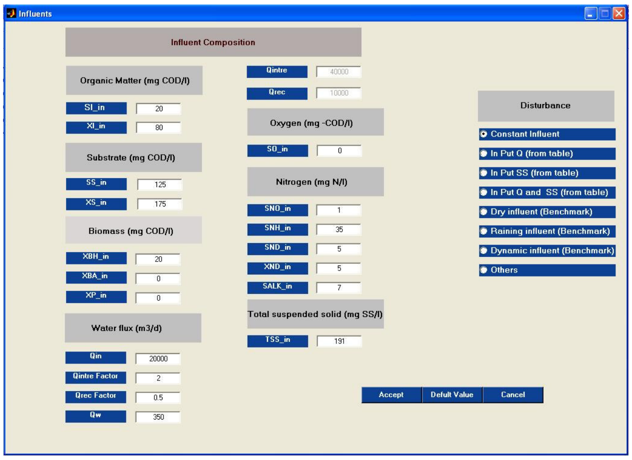

Figure 3.5 Plant Modification Interface.

Integrated Design Procedure According to the Tool

The Integrated Design Procedure starts with the selection of the plant configuration, the tool offers various common configurations of plants with or without N removal, after the plant configuration, the user should select the control structure and type that want to use (in the tool there are various types of controller PID, MPC, GMV, Adaptive...etc). At this stage the user know what configuration and control system he will use, depending on what the user choose the tool activate or deactivate some options and some menus.
At this stage, the tool loads a plant with the same specification that the user chose, this plant call Default Plant. At this stage the user can:

- Modify the plant data which include, the input data, type of perturbations the user want to use, objective function’s formula and associated weights, initial values of state variables and corresponding initial values of selected controller, upper and lower limits, physical constrains, operational constrains, and controllability constrains. In all the interfaces for the plant data modifications, the user can save the modification, set the default values, or cancel the modification that he did. Figure 3.5
- The user can optimize directly with the loaded plant parameters, but he also can loads new plant parameters saved in folders, or loads the parameters of optimized plants, also the user can save plant parameters, save the session, or exit the program.
- User also can modify the optimization method that the tool will use; the tool contains 4 optimization methods, SQP (the default optimization methods that the tool uses), Genetic Algorithm, Simulated Annealing, and hybrid method. For each optimization method, user should determine the parameters of each method, in the SQP case, the user should determine the simulation time, number of iteration of the plant optimization, number of iteration for the controller optimization, and the global iteration for the optimization process.

- After the modification process, the optimization process starts calling a MATLAB file (Prinicpal.mat) where the optimization algorithm execute and the optimization results obtained.
- After the end of the optimization process, the user can simulate choosing other perturbation, plot the simulation results, like for example the substrate graphic, biomass graphic, visualize the optimization results (dimension and operating point), calculation of cost and controllability index (ISE. H∞) , save the optimization results, save the plant parameters, compare the obtained results with the results obtained from other optimization process of plants from the same configuration, the user also can go back to main menu, or exit the program.

Simulation Module

The simulation procedure starts with choosing the plant configuration (plants with/without N removal), after that a default defined plant be loaded by the tool, where the user can simulate directly without any modifications, user can modify:

- The plant data which include the input data and the perturbation type, tank operating point, settler operating point, model parameters and dimension.

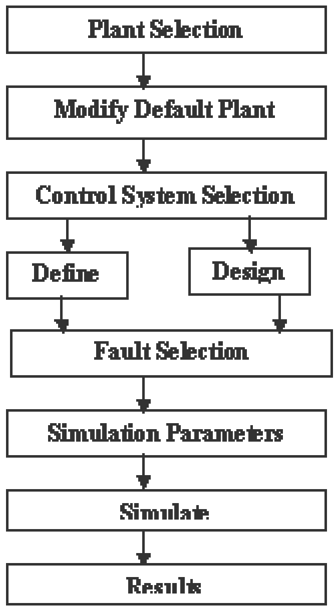

Figure 3.6 General Scheme of the Simulation Module.

- User can choose between set a control system or design a control system (if the user chooses design control system option, the tool enter to control system design which we will explain later) the user chooses the control structures (which means to choose the controller configuration, what variable to measure and what variable to manipulate, what to control (Oxygen or Nitrogen)) and controller type (PID, MPC, GMV, Adaptive…etc)

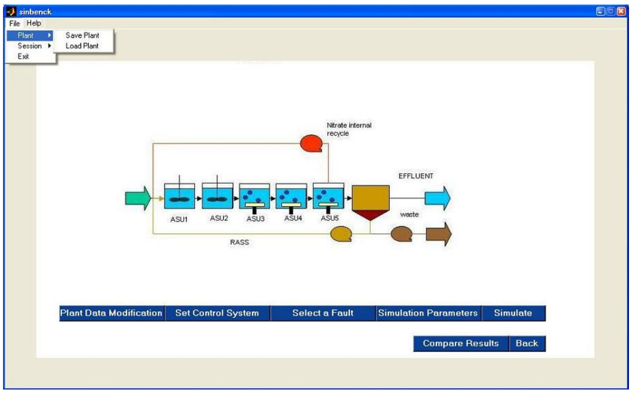

Figure 3.7 Simulation Module Main Interface.

- User can choose if he want to simulate with or without fault, the tool contains the most common faults that usually occur in the WWTP like Toxicity Shock, Inhabitation, Bulking, and Sensor Faults. For each fault user should determine the type, magnitude, and the duration of the fault.
- User also can modify the simulation parameters, which include, the simulation time, the interval time, and steady state time.
- After the simulation process the user can, plot the obtained results, compare the obtained results with other simulation results, save the results, go back to main menu, or exit the program.

Control System Design Module

The Control Module includes Generalized Minimum Variance PID Control (Vega et al., 1991), Generalized Minimum Variance Control (Clarke and Gawthroop, 1975), Generalized Predictive Control (Clarke et al., 1987) and Multivariable Predictive Control (Maciejowsky, 2002). Each control strategy can operate in continuous identification mode or self tuned (identification on demand) mode.
There are three design options on every control strategy: plant model identification (identification layout on Figure 13), controller parameters estimation and identification and control calculation altogether. First of all, for any cased to be simulated, the simulation parameters have to be entered; these include simulation time, sample time, step size (for control evaluation), noise power factor, input mean value (steady state) and output mean value (steady state).

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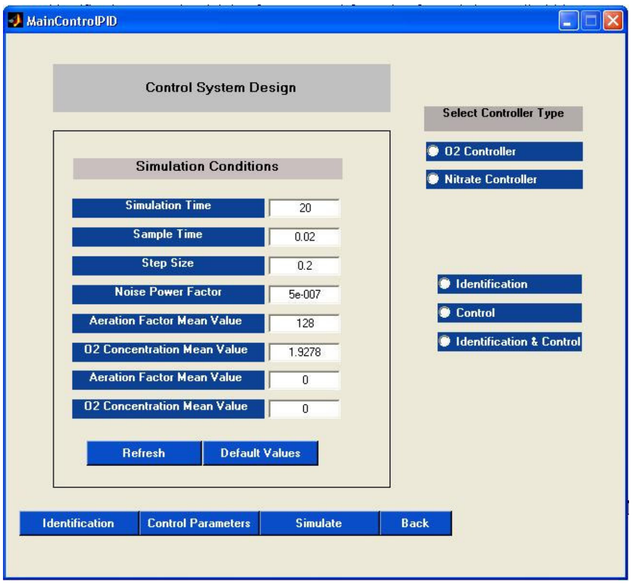

Figure 3.8 Control Design Main Interface

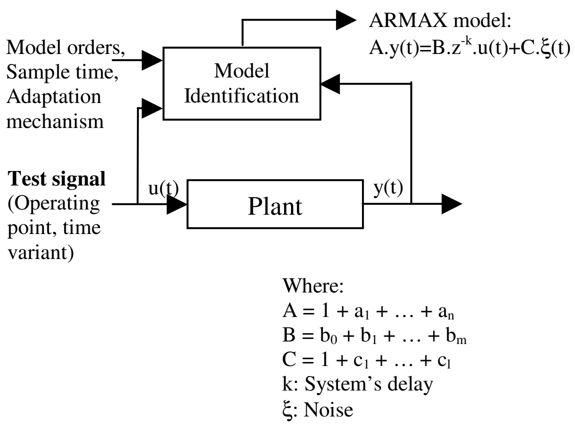

Figure 3.9 ARMAX model identification.

Once these parameters have been established, there are three options for simulation:

- First, for identification purposes, the user must introduce the ARMAX model orders (N, M, L and k), adaptation mechanism, adaptation gain and initial and final time for identification so the ARMAX parameters and the plant output prediction can be calculated.

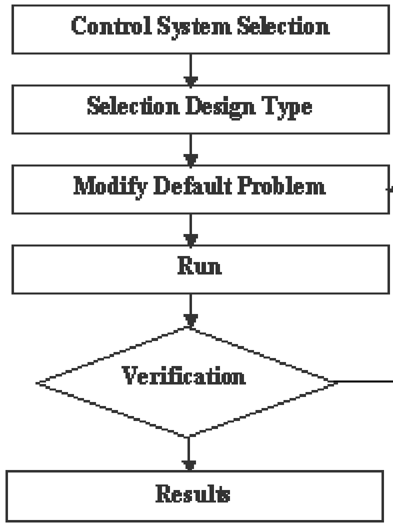

Figure 3.10 General Schema of the Control Design Module.

- In the second case, the controller is estimated from a fixed ARMAX model given by the user, introducing the control parameters depending on the selected algorithm and the initial and final time for control calculation.
- Finally, the third option allows for complete model identification and calculation of the controller. Figure 3.11 represents the adaptive PID controller option (Vega et al, 1991). In this case, the parameters needed are model orders, adaptation mechanism (identification), adaptation gain (identification), initial and final time for identification, control weighting factor, control forgetting factor (when applicable) and the initial and final time for control calculation.

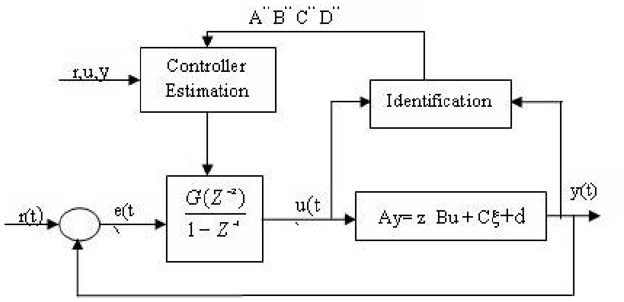

Figure 3.11 Adaptive PID controller.

Once the simulation is done, the results are shown graphically for assessment. The user can pan and zoom graphics and save the results.

Integrated Design Example

Although the original wastewater treatment plant comprises several steps, we will focus on the aerobic treatment-activated sludge and clarification processes.
For open loop design, optimisation of function (1) is sufficient, but for closed loop integrated design, the optimisation procedure involves the two cost functions.

$$f_1(x) = w_1 \cdot v^2 + w_2 \cdot A^2 + w_3 \cdot fk^2 + w_4 \cdot q_2^2$$
$$f_2(x) = w_5 \cdot ISE$$

Process constraints:

- Residence times and mass loads in the aeration tanks:

$$2.5 \le \frac{v}{q} \le 8$$

Constraints on the non-linear differential equations of the plant model to obtain a solution close to a steady state (e close to zero):

$$\left|\frac{dx_1}{dt}\right| = \left|\mu_{\max} y \frac{s_1 x_1}{(K_s + s_1)} - K_d \frac{x_1^2}{s_1} - K_c x_1 + \frac{q}{v}(xir - x_1)\right| \le \varepsilon$$

Controllability constraints:
The controllability constraints are stated to guarantee disturbance rejection capability, either in open or closed loop configurations.

- The ISE norm

$$ISE = \int_{t=0}^{T\max} (s_{1r} - s_1)^2 \cdot dt$$

Where T_{max} =165 hours is the simulation time and s1r is the steady-state value or reference for substrate.

4. Results

Integrated Design Case

Four scenarios are presented to study the integrated design problem and the effectiveness of the algorithms used in tool. First, the design was performed to optimise investment and operation costs without any controllability considerations. The second case is focused in open loop design including disturbance sensitivity gains and $H\infty$ norm as controllability measures, the integrated design of the plant with a PI controller is developed. Finally the integrated design for MPC is shown. For the four design cases, results with deterministic and stochastic methods are presented, and also results using the hybrid methodology (AG refined) available in the tool.

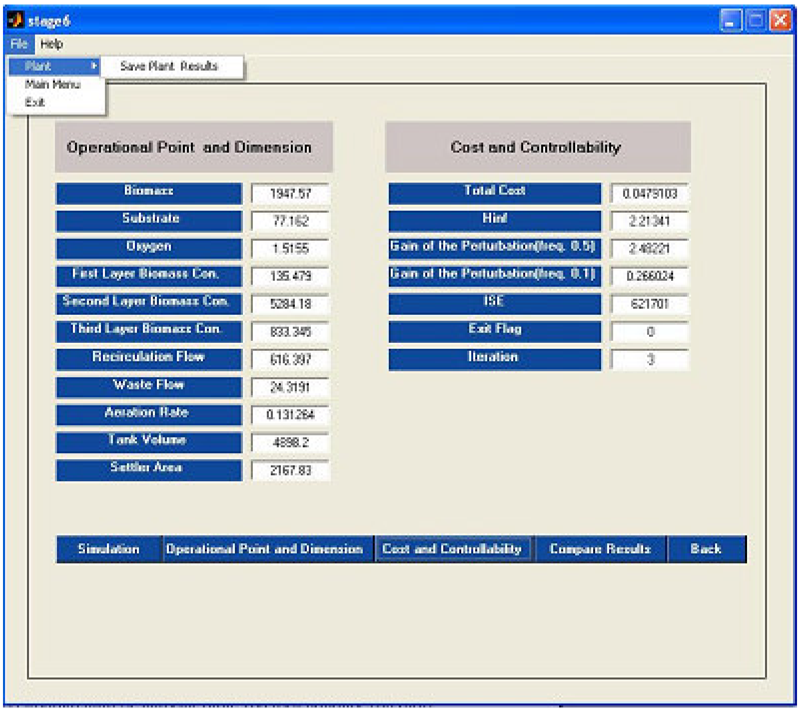

Figure 4.1 Integrated Design Results

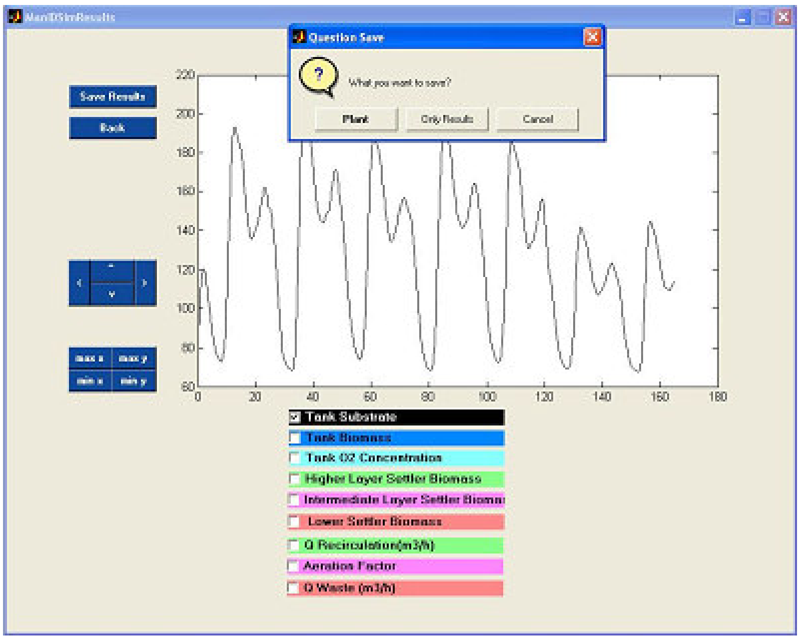

Figure 4.2 Integrated Design Simulation Results

Simulation Case Study

In this case, we will show the effect of three of most common faults by simulation, which are, Toxicity Shock, Inhabitation, and Bulking, in all the cases the simulation time will be 150 days, the fault will occurs on the 20th day and its effect will finish on the 40th day of simulation and the fault magnitude will be high, in all case the effect of the fault and its interpretation will be shown.

Case 1. Toxicity Shock:
This fault usually occurs when there is some toxicity material in the influent, and a chemical substance stop the biomass growth process, as a results the substrate concentration increase because we biomass does not growth. Figure 4.3 shows the effect of the Toxicity shock in the substrate concentration.

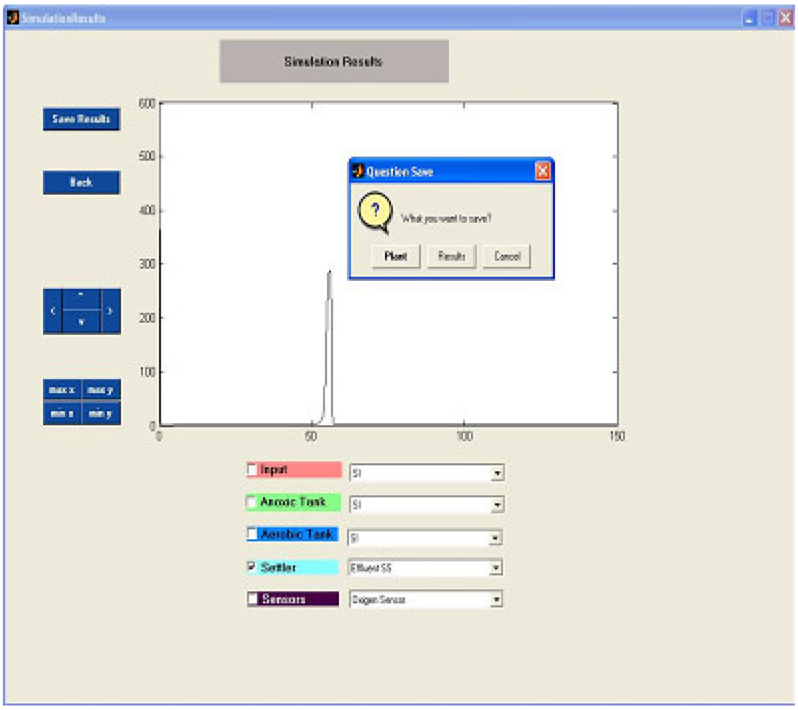

Figure 4.3 Fault Simulation Results (Toxicity Shock)

Case 2: Inhabitation.
It has the same symptom of the toxicity shock, but the chemical substance not only stops the biomass growth, but also kills them, the fault effect is higher than in the toxicity shock.

Case 3: Bulking.
This fault occurs when the type of bacteria change because of certain conditions, and this lead that the sedimentation velocity decrease, and concentration of Total

Suspended Solid (TSS) in the last layer of the settler decrease, and the output substrate increase. Fig 16 shows the effect of the Bulking.

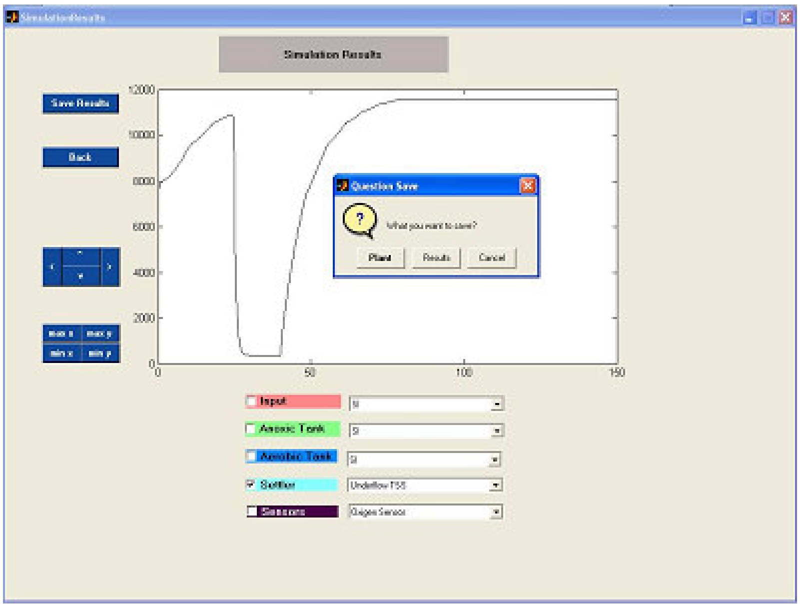

Figure 4.4 Fault Simulation Results (Bulking)

Control Design Case Study:

The results discussed in this section refer to discrete adaptive PID controller design for controller parameters evaluation, plant model identification, control parameters calculation and identification and control calculation altogether. The Simulation conditions for each case are the same, Simulation time: 28 days, Sample time: 0,02 days, Step size: 0,2 (corresponds to 10% for DRBS in identification and control calculations), Noise power-factor: $5x10^{-7}$, input mean value: 7,5 h^{-1} and output mean value: 3,73 g O_2/m^3.

Case 1: Controller Parameters Evaluation.
The simplest case for simulation is this where the user introduces the values of the discrete PID controller (g_0, g_1 and g_2) and simulates the closed loop response of the plant. The results show the reference (step), plant input and output (step response)

Case 2: Plant Model Identification.
This case is intended purely for modelling the plant. The user introduces the orders of the ARMAX model to be calculated, the adaptation mechanism to use and its gain and the initial and final time for identification. The results show the ARMAX parameters (A_n, B_m, and C_l) evolution and the model predicted output to a DRBS input.

Case 3: Control Parameter Calculation.

In this option, the ARMAX model of the plant, the forgetting and the weighting factors (for control purposes) are needed. After simulation, the results show the evolution of the estimated controller parameters, the controller output estimation, the response of the plant to a DRBS and a step input, the input signal and the control signal.

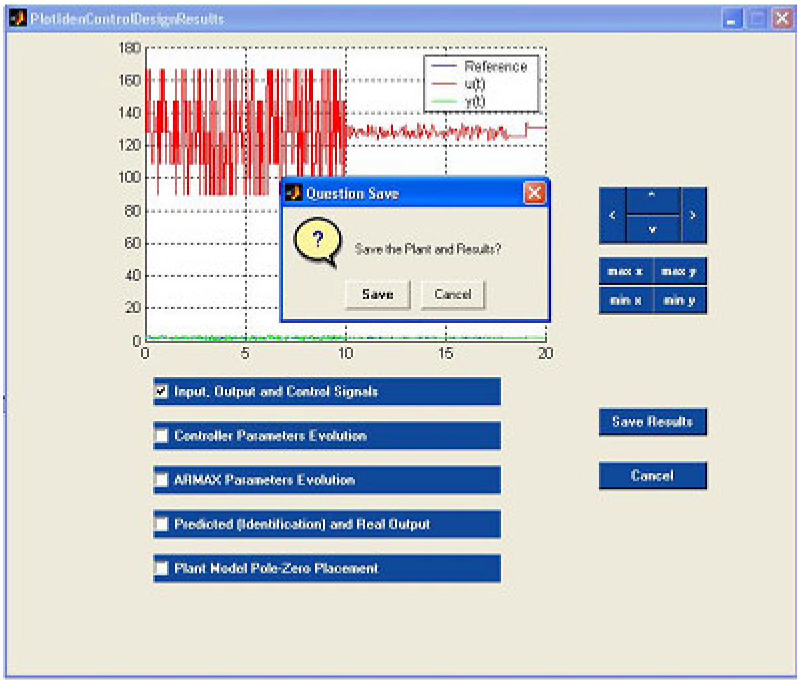

Figure 4.5 Identification and Control Results

For this option the parameters of cases 3 and 4 are needed. For better results, the control estimation should start (control initial time) after identification has been – at least partially – achieved. The results include model parameters evolution, plant model zero-poles placement, model output prediction, controller parameters evolution, controller output estimation, input signal, output signal and control signal.

5. Conclusion

As we can see from the case studies, the tool showed its efficiency as a support tool as support tool for the integrated design process or for the simulation process. The tool integrated the most common optimisation methods, and applied the control systems which shown there efficiency in the control process of activated sludge process.

Using the tool make the Integrated Design process easier and friendly. Advantages achieved by using user interface were making the data entry, and getting results process easy and understandable. Work is going on the improvement of this support tool adding more modules for the fault detection and diagnosis, control system design, and synthesis calculations. Many private companies are interesting in the marketing of this tool after an extends developing phase.

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Reference

Seferlis, P., Georgiadis, M,. (2004). The Integration of Process Design and Control.

Jussi H., Juha H., Jussi M., (2005). An integrated multiobjective design tool for process design, Applied Thermal Engineering

Pajula, E., Ritala, R., (2006). Measurement uncertainty in integrated control and process design -a case study, Chemical Engineering and Processing.

Chooa, H., Hammondb, J., Tommeleinc, D., Austine,A., 1, Ballard, G., (2004). DePlan: a tool for integrated design management, Automation in Construction

Lim, Y., Floquet, P., Joulia, X., Kim, S., (1999). Multiobjective optimization in terms of economics and potential environment impact for process design and analysis in a chemical process simulator, Industrial and Engineering Chemistry Research

Umeda, T., Kuriyama, T., Kobayashi, S., Ichikawa, A., (1980). Interactive solution to multiple criteria problems in chemical process design, Computers and Chemical Engineering.

Clark, P., Westerberg, A., (1983). Optimization for design problems having more than one objective, Computers and Chemical Engineering.

Samuelson, P., (2005). Control of Nitrogen Removal in Activated Sludge Process, Ph.D. Thesis, Uppsala University

Edgar, T., Himmelblau, D., (2001). Optimization of Chemical Processes. Mc Graw Hill.

Gen, M., Chen, R., (2000). Genetic algorithms and engineering optimization. John Wiley and Sons.

Gill, P., Murray, W., Wright, M., (1981). Practical Optimization. Academic Press

Salamon, P. Sibani, P., Frost, R. (2002). Facts, Conjectures, and Improvements for Simulated Annealing. SIAM monographs on Mathematical Modeling and Computation

Laarhoven, P., Aarts, E., (1987) Simulated Annealing: Theory and Applications. Kluwer Academic Publishers

Costa, L., Oliveira, P., (2001). Evolutionary Algorithms Approach to the Solution of Mixed Integer Non-Linear Programming Problems. Comp. Chem. Eng.

Tsai, M.,Chang, C., (2001). Water usage and treatment network design using genetic algorithms. Ind. Eng. Chem. Res.

Revollar, S., Vega, P., Lamanna, R. (2004). Algorithmic synthesis and integrated design of chemical reactor systems using genetic algorithms. World Automation Conference. Sevilla.

Vega, P., Prada, C., Aleixandre V., (1991). Self-tuning predictive PID controller. IEE Proceedings.

Clarke, D., Gawthroop, P.J., (1975). Self-tuning controller, IEE Proc..

Clarke, D., Mohtadi, C., Tuffs, P., (1987). Generalized Predictive Control. Part I. The Basic Algorithm. Automatica.

Maciejowsky J., 2002. Predictive Control: with constraints. Pearson Educated Ltd,

Revollar S., Lamanna R., Vega, P., (2004). Algorithmic Synthesis And Integrated Design of Chemical Reactor Systems Using Genetic Algorithms. IEEE.

Pérez, O., Colmenares, W., Granado, E., Vega P., Francisco, M., (2004). Integrated System Design with Standard Industrial Controllers via LMIS. IEEE