Proceedings of the 9th International Symposium on
Dynamics and Control of Process Systems (DYCOPS 2010),
Leuven, Belgium, July 5-7, 2010
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A New Cost-Optimal and Fault-Tolerant Instrumentation Sensor Network Design Methodology for Chemical Plants

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Abstract: In this paper, an optimal redundant instrumentation sensor network design methodology is presented for complex chemical process plants using a combinatorial particle swarm optimization search (CPSO) engine. The approach, which is more flexible and general in comparison with previous works, aims to minimize cost as a main design factor, similar to the usual trend in the literature. Besides, it caters for fault-tolerance issue as a crucially important feature in the design procedure which has not been addressed sufficiently in the reported research works. For this purpose, weak redundancy degree (WRD) and sensor network reliability (R) are incorporated in the proposed design scheme as three evaluating measures. This enables the designer to maintain a desired fault-tolerant redundancy in the proposed sensor network to cope with a possible set of sensor failures. Thus, the developed CPSO engine searches in a diverse variety of sensor networks to adopt the most fitted one based on the imposed fault-tolerant design constraints. This facilitates the network realization of the fault-tolerance as the most attractive feature which is practically very demanding. Implementation of the proposed design methodology is illustrated in a simulated continuous stirred tank reactor (CSTR) as a benchmark process plant used in a large-scale design to show its effective capabilities.

1. INTRODUCTION

Measurements of all process variables are not practically cost-effective and yet operationally feasible in complex industrial plants. Accordingly, only a limited number of process variables are decided to be measured directly and hence reconciliation techniques could be beneficial for estimating the non-measured variables using the process model dynamics. Generally, a sensor network design methodology mainly deal with location or/and precision of sensors in large-scale plants so that some desired criteria, viz: observability (Vaclaveck and Loucka, 1976), precision (Musiln et al., 2005) and (Bagajewicz and Cabrera, 2002), reliability of estimation of variables (Ali and Narasimhan, 1993), (Ali and Narasimhan, 1995) and gross and error detectability (Bhushan and Rengaswamy, 2000a), (Raghuraj et al., 1999) are satisfied.

Bagajewicz (1997) used a tree type enumeration procedure to design a minimal cost network subject to constraints on precision, availability, resilience and error detectability. He proposed a design strategy that incorporates these criteria simultaneously for linear systems and suggested a MINLP to solve the problem. Further, Bagajewicz and Sanchez (1999) showed that problem of minimizing the variance subject to cost constraint can be converted to the problem of minimizing the cost subject to the variance constraints via determining measurement locations in linear networks. Bagajewicz and Cabrera (2002) presented a new MILP formulation, replacing the previous tree search solution procedures for minimizing cost subject to explicit constraints of precision, error detectability, resilience and availability. Although their method works well for small and medium problems, for large size problems the challenge exists. Sen et al. (1998) integrated graph theory and genetic algorithm concepts to develop a generalized sensor network design algorithm for non-redundant linear mass flow processes. In comparison with graph-theoretic algorithms (Ali and Narasimhan, 1993), GA-based method (Sen et al.,1998) provides more near optimal solutions (Sen et al.,1998). Bagajewicz et al. (2004) developed an instrumentation network design scheme that could reflect the potential benefit of adding sensors in networks and used value and cost concepts separately and applied them both in the integrated design, enabling to satisfy fault detection, material accounting and control criteria simultaneously. Kotecha et al. (2008) proposed a duality between the precision and reliability problems for non-redundant sensor network design in linear processes. This method enables one to convert any reliability design measure to precision framework and use explicit optimization algorithm, which was already developed for precise design (Bagajewicz and Cabrera, 2002), to design sensor network in the precision domain, satisfying reliability constraints specified in the design.

Only a few works have addressed the sensor network design by determining both type and location of sensor simultaneously; Muslin et al. (2005) discussed both location and type of sensors in precise linear sensor network designs. If type of sensors is not a consideration in design procedure, number of possible networks that can be constructed via given set of sensors decreases drastically. Observing this point, i.e. neglecting the variety of sensors in the design procedure can lead to a substantial saving of design time. Subsequently, designer can take advantage of the saved time to study on designs developed by enumeration methods. Enumeration methods try to examine all possible candidates based on a logical algorithm, and suggest the most optimal solution whose optimality is guaranteed because of their inherit analytical behavior. This may be the main reason behind previous works that have ignored sensor variety in their presented design.

Staroswieck et al (2004) addressed the problem of fault tolerant estimation and the design of fault tolerant sensor networks. They defined fault tolerance with respect to a principle that a given functional of the system state should remain observable when sensor failures occur. All sensor sets were shown in an automaton which contains all the subsets of sensors such that the estimation objective can be achieved. They introduced three criteria evaluating the system fault tolerance with respect to sensor failures when a reconfiguration strategy is used: weak redundancy degree (RD), sensor network reliability (R), and mean time to non-observability (MTTNO). Sensor networks are designed by finding redundant sensor sets whose RD and/or R and/or MTTNO are larger than some specified values. Their regressive method works well on small designs in which design algorithm only cares about the existence of a sensor on the variable. However, when it comes to designing of networks with multiple sensors available to measure a variable, due to the drastic increase of number of possible solutions, the calculation effort highly increases and it fails to work. In addition, a main criterion in instrumentation design procedure, i.e. cost of instrumentation, has been neglected in this approach.

In order to address the mentioned issues altogether, we have presented a new instrumentation design methodology for cost-optimal and fault-tolerant sensor networks which is more comprehensive, flexible and practical than other designs given in the literature. In the proposed method, instead of following the regressive method which uses a regular and determined approach to check all the possible nodes that fulfill the constraints, a search engine is used. In this method, search engine does not examine all solutions to find the most optimal one, so time consumption decreases considerably. This is a benefit that allows designer to involve more variety of sensors in design in addition to facilitating the design to be applied in large-scale designs for the sake of saved time caused by using the CPSO. Moreover, cost-related considerations as well as the fault tolerance criteria have been involved in the design procedure.

In this paper, first the necessary terms, e.g. redundancy degree and reliability of networks, are briefly introduced (Staroswieck et al, 2004). The proposed fault tolerant estimation design algorithm is presented in the next section. Finally, the presented algorithm is implemented in a CSTR case study including a set of 15 process variables to illustrate its specified capabilities.

2. FAULT TOLERANCE ASSESSMENT

2.1 Minamility and Redundancy

Consider the continuous time deterministic system:

$$\dot{x} = f(x(t), u(t)) \tag{1}$$

$$y(t)=g(x(t)) \tag{2}$$

$$z(t)=h(x(t)) \tag{3}$$

where $x \in R^n$ is the state vector, $u \in R^m$ is the control input, $y \in R^p$ is the measurement vector, and $z \in R^q$ is the functional of the state which is to be estimated. The inputs u(t) are assumed to be sufficiently differentiable and f, g, h are sufficiently smooth vector fields. Let $J \subseteq R$ be a subset of the system sensors, and introduce the notation obsv(z/J) where (for a given definition of observability):

$$obsv(z/J)=\begin{cases}1 & if\ z\ \ is\, observable\, with\, J\\ 0 & otherwise\end{cases} \tag{4}$$

Let 2^R be the set of all subsets of R; then (4) induces a two-class partition:

$$\begin{aligned} 2^{R+} &= \{J \subseteq R;\, obsv(z/J)=1\} \\ 2^{R-} &= \{J \subseteq R;\, obsv(z/J)=0\} \end{aligned} \tag{5}$$

The class 2^{R+} contains all the subsets of sensors by which z is observable, and it is assumed that $R \in 2^{R+}$; i.e. the system is observable by the whole set of sensors. Accordingly, minimal sensor set and redundant sensor sets are defined a following: A subset of sensors $J \in 2^{R+}$ is minimal (MSS), if

$$\forall k \subset J \quad k \notin 2^{R+} \tag{6}$$

and a subset of sensors $J \in 2^{R+}$ is redundant (RSS), iff it is not minimal.

2.2 Interpretation of fault tolerance

Assume that one or several sensor failures occur at time t_f so that the set of sensors J can be decomposed into the normal and the faulty ones: $J = J_n \cup J_f$. Therefore, the measurement equations can be written

$$y_n(t) = g_n(x(t)) \tag{7}$$

$$y_f(t) = g_f(x(t)) \tag{8}$$

where y_n (resp. y_f) represent the normal (resp. the faulty) outputs of the sensor network J and g_n (resp. g_f) are the normal (resp. the faulty) measurement equations. The fault tolerance problem used in this paper can be interpreted as follows: the faulty sensors J_f are switched off, and the problem is to assess the possibility of still estimating the functional z by using the remaining set of sensors J_n which is indeed true, provided system is still observable. This method that is named reconfiguration strategy only needs fault detection and isolation (fault estimation is not necessary), and that the fault tolerance property is a structural one, since it is associated with triple (1), (7) and (8), it does not depend on the type of fault which affects the sensors J_f, In this paper, we consider only the reconfiguration strategy. Now that the interpretation of fault tolerance was presented, the redundancy degree and reliability are defined in the next sections.

2.3 Weak Redundancy Degree

Let $J \subseteq I$ be any subset of the sensors, i.e. some state of the system instrumentation. Let $K \in MSS(J)$, then the quantity $|J \backslash K|$ represents the maximal number of sensors which can be lost while z can still be estimated by K. In the 'best' situation, as many sensor losses as

$$|J| - \min_{K \in MSS(J)} |K| \tag{9}$$

can be accepted. The weak redundancy degree evaluates the size of this 'best' situation.

The weak redundancy degree associated with the pair (z, J) is

$$WRD(z,J) = |J| - \min_{K \in MSS(J)} |K| \tag{10}$$

From the interpretation of $WRD(z,J)$ it follows that the following statement is true:

$$\begin{aligned} &\exists J' \subset J \text{ such that } |J \setminus J'| = WRD(z,J) \\ &\text{and } J' \in MSS(J) \end{aligned} \tag{11}$$

Of course, in many cases, z will no longer be observable after less than $WRZ(z,J)$ sensors are lost.

2.4 Availability of the Estimation Service

Let t_0=0 be the time at which the system operation was started, and let J(t) be the subset of the non-faulty (available) sensors at time t. Let J_0 =J(0), assuming such data to be available, the fault tolerance of the z-estimation process can be evaluated by the probability for the estimation of z to be possible during the given time interval [0,*t*] assuming that it was possible using the set J_0 at time 0, R(z/J_0). Let $K \subseteq J_0$ be any subset of sensors. The probability for the estimation of z to be possible during the time interval [0, t] using K is given by (12):

$$R(z/K,t) = P(z/K).R(K,t) \tag{12}$$

where $P(z/K) = 1$ if K is a MSS or a RSS and $P(z/K) = 0$ otherwise, and $R(K,t)$ is the reliability of the set of sensors K; which is defined as the probability that no sensor of K fails during the interval [0,t]. If sensor failures are independent, i.e. there is no common mode failure, one has

$$R(K,t) = \prod_{k \in K} R_k(t) \prod_{k \notin K} (1 - R_k(t)) \tag{13}$$

where $R_k(t)$ is sensor k reliability. The reliability of such individual components is often modeled using the Poisson distribution:

$$R_k(t) = e^{-\lambda_k t} \tag{14}$$

where λ_k is sensor k failure rate, which is supposed to be constant.

Now, considering the whole set J_0; it follows from the fact that all its subsets K are exclusive, that the probability for the estimation of z to be possible during the time interval [0,t] is given by

$$R(z/J_0,t) = \sum_{K \subseteq J_0} P(z/K)R(K,t) \tag{15}$$

In (15), $P(z/K)$ is 1 if subset K is observable and 0 if not.

3. DESIGN PROCEDURE

Cost, precision and reliability are fundamental characteristics of an instrumentation network. Accordingly, different models can be constructed by employing any combination of these networks. One common model which has been used commonly in the literature minimizes cost of constructing satisfying network reliability and fault tolerance constraints. This model is called minimum cost model and can be shown by:

$$\begin{aligned} &Min \sum_j (C_j S_{ji}) \\ &S_{ji} \in \{0,1\} \qquad S.t. \begin{cases} R(n\text{etwork}) \geq R^* \\ WRD \geq WRD^* \end{cases} \end{aligned} \tag{16}$$

where S_{ji} represents the integer number showing the placement of the variable of sensor type j at network location i.The reliability of the network should be evaluated according to the specified variables which should be observed. These variables can be either whole or part of the network states. If the case study is not large, the best solution to these types of optimization problems is using the bottom to top algorithm introduced in (Staroswiecki et al., 2004). In large-scaled or medium-scaled plants, where there are a lot of topologies to study, implementing such algorithms takes a lot of time and fails to be successful. In order to solve this problem, a search engine is used to investigate possible solutions and determine which network is the most optimized solution to the model (16). Note that although the algorithm suggested in (Staroswiecki et al., 2004) for fault tolerant instrumentation is not directly stated as the optimization problem, it can be considered a special case of model (16). Consider that the price of all sensors is equal.

$$C_j = C \quad for\ j = 1,2,...,n \tag{17}$$

In this case, overall cost of a network which has n variables to be measured is:

$$Total\ Cost = \sum_j (C_j S_{ji}) = n.C \tag{18}$$

Therefore, minimizing the number of sensors (n) used in (Staroswiecki et al., 2004) is equivalent to minimizing the cost of sensors, i.e. the model used in (Staroswiecki et al., 2004) can be considered as a special case of model (16).

To solve the presented model in (16), a combinatorial search engine, CPSO (Jaboui et al., 2004), is proposed to search for the best solution satisfying the optimization problem. The block diagram of such an algorithm has been depicted in Fig. 1. CPSO will check observability, redundancy degree and reliability of the network for every particle in each iteration. If these values fulfill the problem requirements, CPSO allows the particle to survive in the engine; otherwise, it will put away the particle and choose another one as a substitute. This scenario goes on until the best solution is suggested by CPSO.

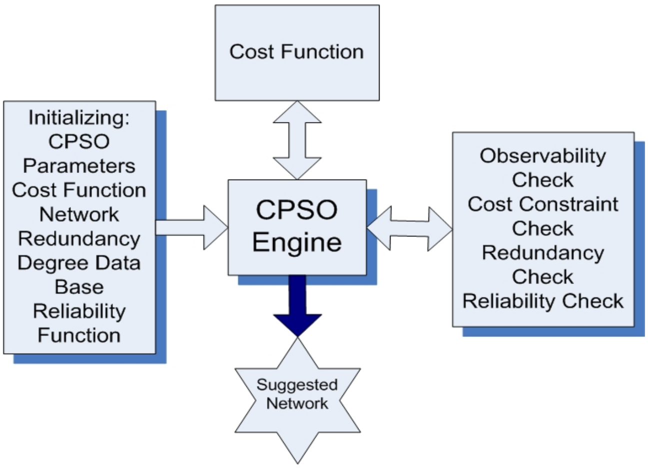

Fig. 1. Block Diagram of the design algorithm aims to search a network satisfying (16)

4. IMPLEMNTATION ON THE CASE STUDY AND RESULTS

The case study used in this paper is the CSTR that Bhushan and Rengaswamy (2000b) introduced in their article (Fig. 1). This process involves an exothermic liquid-phase reaction. The model parameters along with their nominal operating values are presented in (Bhushan and Rengaswamy, 2000b). In this case study, the measurable variables are V, C_A, T, T_C, P, F_4, F, F_{vg}, F_c, F_i, T_i, C_{Ai}, T_{ci}, F_2, and F_3. Thus, in order to monitor all variables, five types of sensor are required. To incorporate variety in design, three different sets of sensors are considered for each sensor type. The failure rates along with corresponding costs of these sensors have been tabulated at Table 1. In the final step, an efficient modified CPSO algorithm is used (Jaboui et al., 2004). Parameters of search engine are set as follows: ω=1.1, c_1=0.6, c_2=0.5, υ_{max} = 2, υ_{min} = -2 and α=1.2. Moreover, 20 particles and 100 iterations have been considered to run the CPSO. Now, the proposed design procedure is conducted to solve the problem in model (16) with five different constraints. In all test runs, the WRD constraint is set four. The reliability constraints vary from 0.7 to 0.85, but the first case does not include any reliability constraint. The search is undertaken ten times so that search engine does not fall into local optimization points. The best network among the ten obtained solutions is chosen as the main solution for that design problem. The solution did not necessarily improve with each additional run; among ten obtained solution the most optimized one is chosen as the best candidate. This policy increases the accuracy of the algorithm. The best and worst solutions obtained in each case are tabulated in Table 2. The advantage of using multiple scans instead of one scan can be clearly observed by comparing the two solutions that they are considerably different from each other.

In order to have a visual measure to compare the cost of all the solutions obtained by CPSO with each reliability constraint, a diagram showing the mutual relationship between network costs and their corresponding reliabilities has been provided in Fig. 3. The upper and lower lines that are shown in bold represent the worst and best solutions obtained by CPSO and the other lines shown in green, represent the other 9 solutions. As seen, there is almost a linear relationship between cost and reliability constraint. The diagram maintains its linearity until reliability reaches 0.85. For higher constraint vales, there is a sharp jump. In other words, in order to have an increase of %2 in the reliability of the network at the end point of the diagram, there is an extra cost of $25000!

The proposed CPSO algorithm was utilized to offer the best possible networks enforced to fulfill the requirements of the design problem, but there is no guarantee for the optimality of the obtained solutions and there is no available tool that can assure us the obtained solutions are the optimal network among all the other practical networks that can be built by the given sets of sensors. On the other hand, it should be checked that whether the suggested solution satisfies all the design requirements or not. On the other hand, in these designs, 15 variables should be monitored; so many feasible networks can be constructed by combination of measured variables. Accordingly, performing an exhaustive search to verify the results is not practical. If we consider different possible types of sensors given in Table 1 to measure each variable, there will be 384,422,112 observable networks. The mentioned issues necessitate applying appropriate verification tests on the obtained results. In order to cope with mentioned issue, three tests are conducted to verify whether the obtained solutions satisfy our design requirements or not.

The overall time for conducting such an experiment was 3 h and 27 min. If we assume conducting experiment for one single network through MATLAB software and a machine with 2.5 GHz of CPU and 2 GB of RAM takes 0.1036 sec on average, performing an exhaustive search for such a plant will take more than 460 days!

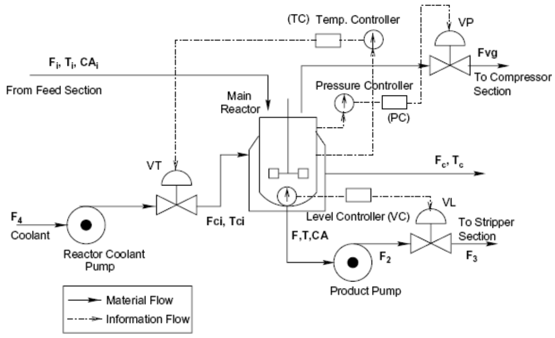

Fig. 2. The schematic diagram of CSTR Process

Table 1. Available sensors for instrumentation design: Volume; C: Concentration; T: Temperature; P: Pressure; F: Flow

	V_1	V_2	V_3	C_1	C_2	C_3	T_1	T_2	T_3	P_1	P_2	P_3	F_1	F_2	F_3
Failure Rate ($\times 10^{-2}$)	1/81	1/50	1/28	1/80	1/50	1/28	1/88	1/49	1/23	1/90	1/48	1/22	1/82	1/44	1/2
Cost ($)	3000	2200	1600	2500	1800	800	1500	1000	400	1400	1000	800	4500	3000	2200

Table 2. The best and worst solutions obtained for different reliability constraints

	V	CA	T	Tc	P	F4	F	Fvg	FC	Fi	Ti	CAi	Tci	F2	F3	WRD*	R*	WRD	R	Cost($)
Best	×	3	3	3	3	3	×	3	×	×	3	3	3	3	3	4	–	4	0.4776	12800
Worst	3	3	×	3	3	3	×	3	3	×	3	×	3	3	2	4	–	4	0.5091	16200
Best	×	3	3	3	3	2	×	3	×	×	2	2	1	2	2	4	0.70	4	0.7098	18100
Worst	×	3	×	3	3	2	1	3	3	×	3	×	3	1	3	4	0.70	4	0.7003	21400
Best	×	3	×	3	1	2	×	3	3	×	2	3	2	2	2	4	0.75	4	0.7529	18600
Worst	×	×	3	3	3	2	×	1	3	3	1	×	2	2	2	4	0.75	4	0.7514	22500
Best	×	3	×	3	1	2	×	3	3	×	2	3	3	1	1	4	0.80	4	0.8024	21100
Worst	×	×	3	3	1	1	×	3	3	×	1	1	3	2	1	4	0.80	4	0.8008	23300
Best	×	3	×	3	1	1	×	3	2	×	2	3	2	1	1	4	0.85	4	0.8510	23900
Worst	×	3	×	2	2	1	×	2	2	2	3	×	2	1	1	4	0.85	4	0.85141	26500

Table 3. Weak redundancy degree verification for five design sets

R.Limit		V	C_A	T	Tc	P	F_4	F	Fvg	F_C	Fi	Ti	C_{Ai}	Tci	F_2	F_3
–	Initial Net	×	3	3	3	3	3	×	3	×	×	3	3	3	3	3
	Last Net	×	**F**	**F**	3	**F**	3	×	3	×	×	3	**F**	3	3	3
0.7	Initial Net	×	3	3	3	3	2	×	3	×	×	2	2	1	2	2
	Last Net	×	**F**	**F**	3	**F**	2	×	3	×	×	2	**F**	1	2	2
0.75	Initial Net	×	3	×	3	1	2	×	3	3	×	2	3	2	2	2
	Last Net	×	**F**	×	3	**F**	2	×	3	3	×	2	**F**	**F**	2	2
0.80	Initial Net	×	3	×	3	1	2	×	3	3	×	2	3	3	1	1
	Last Net	×	**F**	×	3	**F**	2	×	3	3	×	2	**F**	**F**	1	1
0.85	Initial Net	×	3	×	3	1	2	×	3	3	×	2	3	2	1	1
	Last Net	×	**F**	×	3	**F**	2	×	3	3	×	2	**F**	**F**	1	1

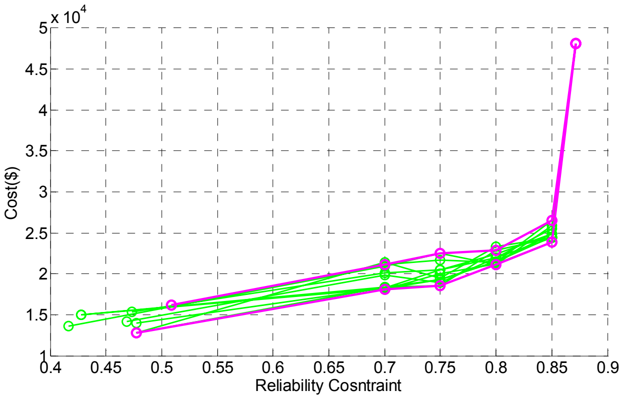

Fig. 3. Cost of the networks versus reliability constraints, the two lines shown in bold are the worst and best solutions

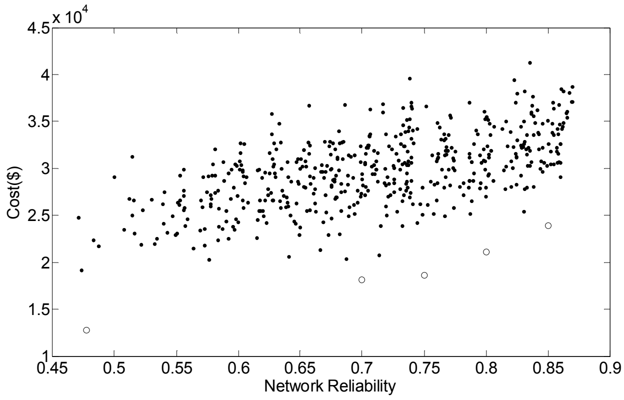

Fig. 4. The validation tests consisting of 500 random networks, the CPSO solutions are recognized by circles

Obviously, it is not possible to perform a comprehensive verification for our design results. However, in order to assess the presented approach performance, 500 randomly chosen networks are shown with their corresponding costs and reliability values in Fig. 4. In this figure the circles represent the solutions suggested by the CPSO that all are below or as high as the dots. Although this type of verification can not completely approve the results, it can lend additional support to the performance of the presented method. Likewise, for reliability validation, we took a number of networks and let their sensors fail according to their reliability values to see whether the new obtained network is observable or not.

In reliability validation, the ratio of the observable network to the total number of networks determines the statistical reliability. The diagram of statistic reliability versus number of experiments for all searches is depicted in Fig. 5. It can be observed that as the number of experiments increases, reliability curve approaches the corresponding reliability constraints. Note that because number of repetitions is not large enough, the statistic reliability obtained with ten test trials cannot be valid for reliability validation, but as more experiments are performed the reliability approaches the expected value.

Reliability and cost validations have been investigated. Table 3 shows the verification results for weak redundancy degree.

For each design, two networks have been shown. The first is the initial one, indicating the main solution suggested by the CPSO algorithm, while the second one represents the network that has been obtained after four sensor failures in the initial network. Examining Table 3 infers that the networks have been remained observable after specified failures appear in the sensor sets. Of course, the networks with fewer failures that are located between these two networks are observable too. For instance, consider the solution suggested by the CPSO in Table 3 for the first design with no reliability constraint in which a sequence of four failures: S_{12}, S_5, S_3 and S_2 can occur in the initial network. In each sensor failure, a new observable network is obtained. This procedure goes on until it reaches a node that has the minimal number of sensors and hence no extra sensor failure can occur, indicating that sequence of failures ends at this node. The number of failures in this sequence determines the weak redundancy degree of initial network which is four in all the designs.

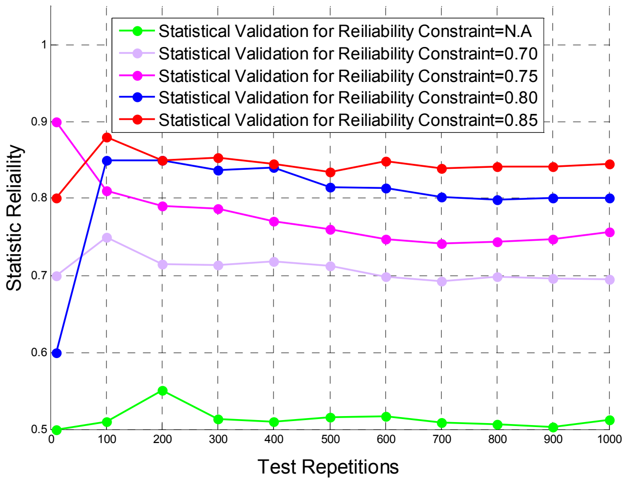

Fig. 5. Statistic Reliability calculated to validate the results, as seen all diagrams approaches the constraints used in the designs as the number of experiments increases

5. COCLUSIONS

A new design methodology has been proposed in this paper based on the CPSO algorithm. This facilitates the employment of a sensor network design perspective to complex large-scale plants in which cost considerations are included as the main design objective while incorporating fault-tolerant properties, leading to a new optimal redundant instrumentation sensor network design. This enables to maintain a desired fault-tolerant redundancy characteristic in a specific industrial environment to cope with a possible set of sensor failures. Different test scenarios carried out in a CSTR benchmark problem illustrated the inherent capabilities of the proposed sensor network design methodology. However, this instrumentation design can be applied in other models with more variable to measure. Instrumentation design for fault tolerant and precise sensor networks is in our line of work at the moment.

REFERENCES

Ali, Y., and S. Narasimhan (1993). Sensor network design for maximizing reliability of linear processes. *AIChE J,* **39**, 820 – 828.

Ali, Y., and S. Narasimhan (1995). Redundant sensor network design for linear processes. *AIChE J,* **41,** 2237 – 2249.

Bagajewicz, M. (1997). Design and retrofit of sensor networks in process plants. *AIChE J*, **43,** 2300–2306.

Bagajewicz, M. and M. Sanchez (1999). Duality of sensor network design models for parameter estimation. *AIChE J*, **45**, 661 – 664.

Bagajewicz, M. and E. Cabrera (2002). New MILP formulation for instrumentation network design and upgrade. *AIChE J*, **48**, 2271–2282.

Bagajewicz, M., D. Chmielewski and R. Rengaswamy (2004). Integrated process sensor network design. Presented at: *The Annual AIChE meeting.* Austin, Texas.

Bhushan, M. and R. Rengaswamy (2000a). Design of sensor network based on the signed directed graph of the process for efficient fault diagnosis. *Ind. Eng. Chem. Res*, 999 – 1019.

Bhushan M. and R. Rengaswamy (2000b). Design of sensor location based on various fault diagnosis observability and reliability criteria. *compt. Chem., Eng.,* **24.**

Jarboui, B., N. Damak, P. Siarry and A. Rebai (2008). A combinatorial particle swarm optimization for solving multi-mode resource-constrained project scheduling problems. *Applied Mathematics and Computation,* **195,** Issue 1, 299 – 308.

Kotecha, P.R, M. Bhushan, R.D. Gudi and M.K, Keshari (2008). A duality based framework for integrating reliability and precision for sensor network design. *Journal of process control,* **18,** 189 – 201.

Musulin, E., C. Benqlilou and M.J. Bagajewicz and L. Puigjaner (2005). Instrumentation design based on optimal Kalman Filtering. *Journal of Process Control,* **15,** 629 – 638.

Raghuraj, R., M. Bhushan and R. Rengaswamy (1999). Location of sensors in complex chemical plants based on fault diagnostic observability criteria. *AIChE J,* **45 (2),** p. 310.

Sen, S., S. Narasimhan and K. Deb (1998). Sensor network design of linear processes using genetic algorithms. *Comput. Chem. Eng,* **22,** 385 – 390.

Staroswiecki, M., G. Hoblos1 and A. Aitouche (2004). Sensor network design for fault tolerant estimation. *Int. J. Adapt. Control Signal Process,* **18,** 55 – 72.

Vaclavek, V. and M. Loucka (1976). Selection of measurements necessary to achieve multicomponent mass balances in chemical plant. *Chem. Eng. Sci,* **31,** 1199 – 1205.