Towards an Improvement of Variable Interaction Identification for Large-Scale Constrained Problems

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***Abstract*—In this work, three modifications are proposed to improve the performance of the Variable Interaction Identification for Constrained problems (VIIC), a technique to detect interacting variables in large scale constrained numerical optimization problems. The changes proposed are: (1) the optimization of a single variable arrangement (the original VIIC needs to find an arrangement of variables for the objective function and also for each constraint), (2) two new strategies to generate a new arrangement, instead of the random generator of the original VIIC, and (3) simulated annealing as an optimizer instead of the greedy search adopted in the original VIIC. The results indicate the viability of using just one variable arrangement and the good performance provided by the two proposed strategies in the search, particularly combined with VIIC's original greedy search.**

***Index Terms*—Large-scale constrained optimization, decomposition method, VIIC, Simulating Annealing**

I. Introduction

When traditional Evolutionary Algorithms (EA's) try to solve large-scale optimization problems, their performance is affected for several reasons, e.g. the search space grows exponentially and its properties may change, the evaluations are usually expensive and when there are interactions among variables the optimization becomes harder. Those issues are commonly categorized in the specialized literature as the "curse of dimensionality" [1], [2], [3].

The divide-and-conquer strategy was introduced by Potter and De Jong [2] with the aim to improve the performance of EA's in large-scale optimization problems. They designed a Cooperative Coevolution (CC) algorithm to improve the performance of the standard Genetic Algorithm. CC requires a method to decompose the problem in sub-problems of less complexity and then optimize each sub-problem by an EA. In the specialized literature, different decomposition methods for unconstrained problems have been developed, e.g., More Frequent Random Grouping proposed by Yang et al.[1], Correlation-based Adaptive Variable Partitioning developed by Yao [4], Quantified Variable Correlations by Hajikolaei et al. [5], Delta Grouping introduced by Omidvar [6], Variable Interaction Learning proposed by Chen et al.[7] and Dependency Identification technique by Sayed [8].

Variable Interaction Identification for Constrained Problems (VIIC) [9] is, to the best of the authors' knowledge, the first decomposition method to solve large scale constrained numerical optimization problems (LSCNOP) and it is an extension of Dependency Identification (DI). The main difference between both methods, is that VIIC creates a decomposition for the objective function and also for each constraint. After that, all variable arrangements are merged to get the final decomposition of the constrained problem. Both, VIIC and DI, perform the decomposition search in a random way, always keeping the best variable arrangement.

This works aims to improve the performance of VIIC by means of three modifications: (1) considering just one variable arrangement in the whole process instead of VIIC's approach of arrangements for the objective function and for each constraint, (2) using two strategies to generate neighbor arrangements based on the current one instead of VIIC's random neighbor generator, and (3) adopting simulating annealing as the search algorithm instead of VIIC's greedy search. Based on those changes, five different algorithms are designed and their performance is evaluated in a recently proposed benchmark for LSCNOP and compared against the original VIIC.

Finally, the scope of this work is to study VIIC's performance to decompose a problem against the algorithms proposed in this paper, leaving the optimization phase to a CC algorithm.

This paper is organized as follows: the background on VIIC decomposition method is described in Section II . The proposed changes and the derived algorithms are presented in Section III. In Section IV the experimental design and parameter setup are shown. The results and conclusions are given in Sections V and VI, respectively.

II. Variable Interaction Identification for Constrained Problems (VIIC)

VIIC provides a way to evaluate the performance of a decomposition for a given large-scale constrained optimization problem [9]. Derived from the definition of "problem separability" [10], a problem can be decomposed into m subgroups of V dependent variables and no variable is present in more than one subgroup. The sum of each subgroup is equals to evaluate the complete solution vector, $(F(\vec{x}) = \sum_{k=1}^{m} F(x_k))$, if m is equal to the dimension of the problem, then the problem is fully separable, in the other hand the problem is partially separable. However, if any variable appears in more than one subgroup, then the subgroups are interdependent and $F(\vec{x}) \neq \sum_{k=1}^{m} F(x_k)$. From those definitions, VIIC is described below.

VIIC uses an initial random arrangement of variable indexes S_g for the objective function and for each constraint to obtain, at the end of the process, a final decision variable index arrangement S_N. This arrangement is used to group the variables into sub-problems with the minimum sub-problem interdependency and with a maximum decision variable interdependency given by $gprs_{diff}$ in Equation 4. Firstly, it is necessary to define the number of subgroups m and the number of variables in each subgroup V. In order to calculate $gprs_{diff}$ in Equation 4, two random values $C_1 > 0$ and $C_2 > 0$ between the boundaries of the problem are required. Next, two vectors with those values are created and evaluated according to Equations 2 and 3, where f is the objective or constraint function to be decomposed. After that, $fit_{all_{C_1C_2}}$ can be calculated by Equation 1. As a second step, $fit_{groups_{C_1C_2}}$ in Equation 5 is calculated by the sum of $fit_{grp_{C_1C_2}=k}$ in Equation 6 for all m subgroups. To calculate $fit_{grp_{C_1}=k}$ in Equation 7 for a subproblem k, the V variables of one subproblem k are set to $C1$, and the rest of the $(N-V)$ variables are set to the other value $C2$ in Equation 8. In the same way, $fit_{grp_{C_2}=k}$ in Equations 9 and 10 is calculated. In Equations 7 and 9, f refers to the objective or constraint function to be decomposed.

$$fit_{all_{C_1C_2}} = m \times [fit_{all_{C_1}} + fit_{all_{C_2}}] \tag{1}$$

$$fit_{all_{C_1}} = f(\vec{x} \mid x_i = C_1, \forall i = [1, N]) \tag{2}$$

$$fit_{all_{C_2}} = f(\vec{x} \mid x_i = C_2, \forall i = [1, N]) \tag{3}$$

$$gprs_{diff} = |fit_{all_{C_1C_2}} - fit_{groups_{C_1C_2}}| \tag{4}$$

$$fit_{groups_{C_1C_2}} = \sum_{k=1}^{m} fit_{grp_{C_1C_2}=k} \tag{5}$$

$$fit_{grp_{C_1C_2}=k} = fit_{C_1grp=k} + fit_{C_2grp=k} \forall k \in m \tag{6}$$

$$fit_{grp_{C_1}=k} = f(\vec{x}_{C_1}) \tag{7}$$

$$x_{C_1} = \begin{cases} C_1 & \forall x \in V \\ C_2 & otherwise \end{cases} \tag{8}$$

$$fit_{grp_{C_2}=k} = f(\vec{x}_{C_2}) \tag{9}$$

$$x_{C_2} = \begin{cases} C_2 & \forall x \in V \\ C_1 & otherwise \end{cases} \tag{10}$$

With all those calculations, one evaluation of an arrangement is performed. The number of random arrangement evaluations is $maxgpr_{iter} = m \times 10^4$. Such number applies for the objective function and also for each constraint, with the goal to get the best decision variable arrangement which minimizes $grps_{diff}$ in Equation 4.

The arrangements for the objective function and for all constraints are stored in a $FrequencyMatrix$ (FM), which is used to get the final decomposition vector S_n. For each subgroup m, the frequency of each variable is stored. After that, those variables with the highest frequency are grouped as shown in Figure 1. The details of VIIC are presented in Algorithm 1.

Algorithm 1 VIIC algorithm

Set $max\_constr = nc$ if there is a feasible solution $max\_constr = nc + 1$
$maxgpr_{iter} = m \times 10^4$, V subset size of m subsets, $c\_num = 0$, $S_N = \emptyset$
while $c\_num < max\_constr$ **do**
    Initialize a random arrangement S_g, generate two random values, $C_1 > 0$ and $C_2 > 0$
    Calculate $fit_{all_{C_1C_2}}$ with Equation 1 and $fit_{grp_{C_1C_2}=k}$ using Equation 6
    Calculate $grps_{diff}$ for arrangement S_g with Equation 4
    while $grps_{diff} \neq 0$ and $gpr_{iter} < maxgpr_{iter}$ **do**
        Generate a new random arrangement S'_g
        Calculate $newgrps_{diff}$ for S'_g
        if $newgrps_{diff} < grps_{diff}$ **then**
            Update $S_g = S'_g$ and $grps_{diff} = newgrps_{diff}$
        end if
    end while
    Add S_g in the c_num row of a Frequency Matrix FM, update $c\_num + 1$
end while
Record the frequency of all variables in each subset of FM
Add the variables of each group with highest frequency to S_N
Return S_N

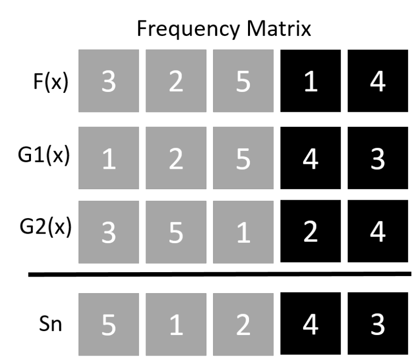

Fig. 1. Example of $FrequencyMatrix$ (FM) for a hypothetical function with five variables, two constraints and $m = 2$. In the first subgroup (in gray) the variables with the highest frequency are 5,1 and 2. In the second subgroup (in black) the most common variables are 4 and 3. Variables 1 and 2 in the second subgroup are discarded because they were assigned to the first subgroup

III. Proposal

VIIC, as other decomposition methods, deal with an optimization problem, i.e., they try to find the best arrangement of variables to decompose a large scale optimization problem. Analyzing the VIIC algorithm, three issues can be considered for improvement:

(a) VIIC optimizes more than one decomposition vector and then merge them into a single one.
(b) The generation of new arrangements in the neighborhood of the current arrangement is performed in a random way.
(c) A greedy search is carried out.

Motivated by the above mentioned issues, the following improvements are proposed.

A. Optimizing a single arrangement

In order to modify the evaluation of a variable arrangement, it is necessary to define a constrained problem:

A constrained numerical optimization problem, without loss of generality, is defined as in Equation 11:

$$\begin{aligned} \text{minimize} \quad & Obj(\vec{x}), \\ \text{subject to :} \quad & \\ & g_i(\vec{x}) \leq 0, \text{ for } i = 1, \ldots, q \\ & h_j(\vec{x}) = 0, \text{ for } j = 1, \ldots, m \end{aligned} \tag{11}$$

where $g_i(\vec{x})$ are inequality constraints and $h_j(\vec{x})$ are equality constraints, q and m are the number of inequality and equality constraints, respectively. The feasible region $\mathbb{F} \subseteq \mathbb{S}$ is defined by the set of all solutions which satisfy all the constraints. Usually, equality constraints are transformed into inequalities constraints of the form $(|h_j(\vec{x})| - \epsilon \leq 0)$ where a small tolerance $\epsilon = 1e^{-4}$ is adopted. A solution is feasible if its constraint violation sum cvs is 0. The cvs is calculated as indicated in Equation 12:

$$cvs(\vec{x}) = \sum_{i}^{q} max(0, g_i(\vec{x})) + \sum_{j}^{m} max(0, |h_j(\vec{x})| - \epsilon) \tag{12}$$

From the definition in Equation 12, and with the aim of considering the constraints into the evaluation, but not each one separately, the cvs can be added as another function besides the objective function. This change allows to optimize a single variables arrangement without loss of generality, while avoiding the frequency matrix required by the original VIIC. Therefore, Equations 2, 3, 7 and 9 are substituted by Equations 13, 14, 15 and 16, respectively.

$$fit_{all_{C_1}} = Obj(\vec{x}) + cvs(\vec{x}) \mid x_i = C_1, \forall i = [1, N] \tag{13}$$
$$fit_{all_{C_2}} = Obj(\vec{x}) + cvs(\vec{x}) \mid x_i = C_2, \forall i = [1, N] \tag{14}$$
$$fit_{grp_{C_1}=k} = Obj(\vec{x}_{C_1}) + cvs(\vec{x}_{C_1}) \tag{15}$$
$$fit_{grp_{C_2}=k} = Obj(\vec{x}_{C_2}) + cvs(\vec{x}_{C_1}) \tag{16}$$

B. Neighborhood strategies

VIIC generates a random arrangement of variables at each iteration to find the best decomposition vector. Therefore, the information of the current arrangement is disregarded. With the aim to create an arrangement but based on the features of the current arrangement, two strategies are developed. In the first one, a random percentage of variables from the whole contents of the current arrangement is selected and such variables are exchanged. On the other hand, in the second strategy, the variables are randomly selected from each subgroup and they are passed to the next subgroup. Both strategies (1 and 2) are depicted in Figures 2 and 3, respectively.

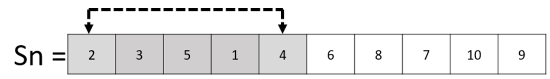

Fig. 2. Strategy 1: Neigborhood strategy based on the whole contents of the current arrangement

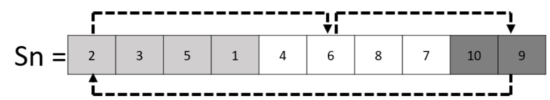

Fig. 3. Strategy 2: Neigborhood strategy based on the subgroups of the current arrangement

C. Simulating Annealing

As it was mentioned early in this paper, the original VIIC adopts a greedy search. However, this kind of search may lead to local optimum solutions. Therefore, in this work such search is replaced by Simulating Annealing (SA). SA, proposed by Kirkpatrick [11], is a probabilistic technique to approximate the global optimum of a function. SA is a trajectory-based algorithm typically applied to combinatorial problems [12]. It starts with a random solution and an initial temperature T. The temperature controls the probability of accepting neighbors whose fitness values do not improve the one of the current solution. At each iteration the temperature T decreases gradually.

D. Improved VIIC versions

The details of the proposed VIIC are presented in Algorithm 2. The main changes with respect to the original VIIC algorithm are marked in bold. The SA behavior is inserted in line 8. From this base algorithm, five versions were developed as described in Table I.

TABLE I
THE FIVE DIFFERENT ALGORITHM VERSIONS PROPOSED AND THEIR STRUCTURE

Algorithm name	Search algorithm	Neigborhood strategy
SA1_VIIC	Simulating Annealing	Strategy 1
SA2_VIIC	Simulating Annealing	Strategy 2
VIIC_F+CVS	Greedy	Random
VIIC_F+CVS_N1	Greedy	Strategy 1
VIIC_F+CVS_N2	Greedy	Strategy 2

IV. EXPERIMENTAL DESIGN

To evaluate the performance of the five proposed versions of the algorithm, a subset of 18 benchmark problems [9] were solved. This is, to the best of the authors' knowledge, the first benchmark for large-scale constrained optimization problems. In Table II the characteristics of each test problem

Algorithm 2 New VIIC algorithm

$maxgpr_{iter} = m * 10^4$, V subset size of m subsets, $c\_num = 0$, $S_N = \emptyset$
Initialize a random arrangement S_n
Generate two random values, $C_1 > 0$ and $C_2 > 0$
Calculate $grps_{diff}$ for S_n arrangement, with Equation 4 considering Equations 13 to 16
while $grps_{diff} \neq 0$ and $gpr_{iter} < maxgpr_{iter}$ **do**
  Generate a new arrangement S'_n with certain neigborhood strategy Figures 2 and 3
  Calculate $newgrps_{diff}$ for S'_n
  if $newgrps_{diff} < grps_{diff}$ **then**
    Update $S_n = S'_n$ and $grps_{diff} = newgrps_{diff}$
  end if
end while
Return S_N

are summarized. The six selected test problems ($F3$, $F6$, $F9$, $F12$, $F15$, and $F18$) correspond to those with three constraints. They were chosen because of their decomposition complexity compared to those with one or two constraints. Twenty-five independent runs per each test problem, over three dimensionalities e.g., 100, 500, and 1000, were carried out. The final variable arrangement S_n for all algorithms was evaluated in both, objective function and constraints in order to compare the decomposition behavior in each constrained problem. Thus, the full experiment is composed of seventy two functions. (six constrained functions with one objective function and three constraints, all of them in three dimensionalities). The 95%-confidence Wilcoxon rank sum test was applied to the samples of results to get statistical support on the findings. The results of the five algorithm versions were compared against those obtained by the original VIIC algorithm.

For all the algorithms compared the number of subgroups was set to $m = 2$. Both neighborhood strategies exchanged 40% of the decision variables. Finally, for those algorithms with SA as the search algorithm, the acceptance initial probability was set to 0.3 and the final probability was set to $1E-3$.

V. Results

The performance comparison in this work was based on evaluating the final and only decomposition arrangement S_n obtained by the five algorithm versions proposed in this work, against the set of decomposition arrangements obtained by the original VIIC (one for the objective function and one for each constraints). It is worth reminding that the set of decomposition arrangements obtained by VIIC are merged at the end to get a single arrangement. However, such arrangement is not evaluated.

To deal with that difference and to promote a fair comparison, the single decomposition arrangement obtained by the proposed algorithm versions is evaluated in the objective function and also in each constraint of the problem. Those results are then compared against those obtained by the evaluation of each arrangement obtained by VIIC for the objective function and for each constraint. The goal is to verify if the single arrangement obtained by the algorithms proposed in this research are competitive against those obtained by VIIC for the objective function and for each constraint.

The statistical results are summarized in Tables III, IV and V for dimensions 100, 500, and 1000, respectively. Those tables include the best, median and standard deviation values by the arrangements obtained by VIIC (one for the objective function and one for each constraint) and by the only arrangement obtained by the five proposed algorithms evaluated in the objective function (obj) and in each constraint (G1, G2, and G3). The evaluation of the single arrangement obtained by the five proposed algorithms is also included in the tables (Sn column).

As a general observation, and somehow expected, the performance of all algorithms, including VIIC, decreases as the dimensionality increases. However, in test problem $F3$ (separable objective function), all algorithms provided competitive decomposition vectors in the three dimensions tested (100, 500, and 1000). On the other hand, for test problems $F12$, $F15$ and $F16$, whose objective functions are the most difficult to solve, all the compared algorithms could not find a suitable decomposition for the objective function. In contrast, competitive decomposition values were found for the constraints.

The number of test problems where each proposed algorithm version outperformed VIIC, based on the 95%-confidence Wilcoxon rank sum test are shown in Figure 4. In the remaining test problems no significant differences were reported. The best performance of VIIC_F+CVS over VIIC suggests that the idea of optimizing a single decomposition arrangement is an viable alternative to obtain competitive results without depending of the frequency matrix. Both, SA1_VIIC and SA2_VIIC, outperformed VIIC in more test problems than VIIC_F+CVS. However, strategy 1 obtained better results than strategy 2 in those algorithms based on SA. Finally, the best overall results were reached by VIIC_F+CVS_N1 and VIIC_F+CVS_N2, i.e., the usage of a greedy search combined with any of the two strategies proposed for neighbor generation seems to be the most suitable for problem decomposition in this set of large-scale constrained optimization problems.

VI. Conclusions

In this work, three modifications to improve the performance of VIIC when solving large-scale constrained optimization problems were proposed. The inclusion of the constraint violation sum in the evaluation of the decomposition vector was the first modification. Such change allowed optimizing one variable arrangement while discarding VIIC's frequency matrix. Instead of the random way to generate new arrangements, two strategies to create new decomposition arrangements based on the features of the current one were proposed. Finally, VIIC's greedy algorithm was changed and Simulating Annealing was used instead. Based on those changes, five

TABLE II
SUMMARY OF THE 18 TEST PROBLEMS. ONLY THOSE WITH THREE CONSTRAINTS WERE SOLVED.

Test problem	Description		Objective	Constraint		Objective	Constraint
$Obj1$	Completely separable	F1	$Obj1$	g_1	F10	$Obj4$	g_1
$Obj2$	Partially Nonseparable	F2		g_1, g_2	F11		g_1, g_2
$Obj3$	Partially Nonseparable	F3		g_1, g_2,g_3	F12		g_1, g_2,g_3
$Obj4$	Partially Nonseparable, Overlapping	F4	$Obj2$	g_1	F13	$Obj5$	g_1
$Obj5$	Spliced nonseparable, Overlapping	F5		g_1, g_2	F14		g_1, g_2
$Obj6$	Spliced nonseparable, Overlapping nonseparable	F6		g_1, g_2,g_3	F15		g_1, g_2,g_3
g_1	Separable groups of 5 variables	F7	$Obj3$	g_1	F16	$Obj6$	g_1
g_2	Nonseparable groups of 3 variables	F8		g_1, g_2	F17		g_1, g_2
g_3	Spliced nonseparable pairs	F9		g_1, g_2,g_3	F18		g_1, g_2,g_3

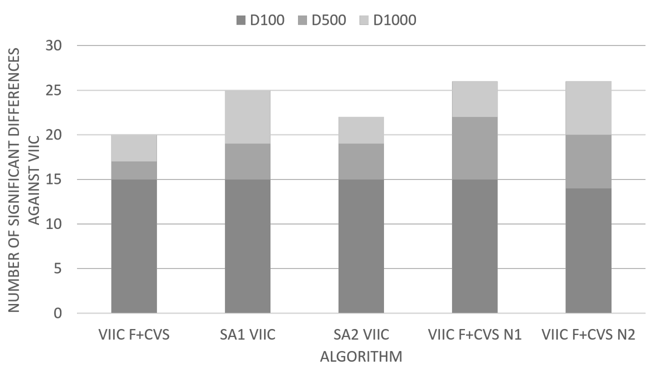

Fig. 4. Summary of Wilcoxon test. The graphic shows the count of significant differences in favor to each algorithm proposed against VIIC

algorithm versions were developed and compared against VIIC. Despite the fact that all compared algorithms, including the original VIIC, were affected in their performance as the dimensionality increased, interesting findings were found. The usage of just one variable arrangement is viable and does not affect, and in fact it improves, the final results. The two strategies to generate new arrangements based on the features of the current one improved the performance of VIIC. Interestingly, they provided better results when combined with the original VIIC's greedy search instead of the proposed SA.

Other population-based metaheuristics could be tested instead of SA and other neighborhood strategies can be implemented. Finally, SA can be revisited to design other temperature variations with the goal to improve its performance.

ACKNOWLEDGMENT

The first author acknowledges support from CONACyT and the University of Veracruz to pursue graduate studies at the Artificial Intelligence Research Center. The second author acknowledges support from CONACyT through project No. 220522.

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TABLE III
Statistical results for dimension 100

			F3					F12			
		Sn	Obj	G1	G2	G3	Sn	Obj	G1	G2	G3
VIIC	Best		**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**		6.17E+05	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median		6.98E-10	**0.00E+00**	**0.00E+00**	6.28E+05		1.35E+08	**0.00E+00**	2.06E+05	**0.00E+00**
	STD		1.30E-09	5.46E-12	8.65E+07	6.87E+07		5.30E+08	4.18E-12	1.01E+08	5.67E+07
SA1_VIIC_F+CVS	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	2.14E+05	7.02E-04	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	4.66E-10	**0.00E+00**	**0.00E+00**	**0.00E+00**	2.82E+08	5.13E+07	**0.00E+00**	**0.00E+00**	**0.00E+00**
	STD	2.11E-06	1.30E-09	4.80E-12	0.00E+00	0.00E+00	6.72E+08	1.14E+08	5.49E-12	5.47E+07	3.87E+07
SA2_VIIC_F+CVS	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	1.76E+05	3.52E+04	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	6.98E-10	**0.00E+00**	**0.00E+00**	**0.00E+00**	3.01E+08	4.56E+07	**0.00E+00**	**0.00E+00**	**0.00E+00**
	STD	1.68E-06	1.09E-09	5.32E-12	**0.00E+00**	**0.00E+00**	9.20E+08	1.62E+08	8.48E-12	7.68E+07	5.53E+07
VIIC_F+CVS	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	7.68E+03	3.05E-05	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	1.16E-09	**0.00E+00**	**0.00E+00**	**0.00E+00**	7.87E+07	5.76E+07	**0.00E+00**	**0.00E+00**	**0.00E+00**
	STD	1.53E-06	1.40E-09	5.07E-12	**0.00E+00**	**0.00E+00**	1.41E+08	1.22E+08	4.44E-12	5.04E+07	1.65E+07
VIIC_F+CVS_N1	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	1.03E+04	1.86E-08	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	4.66E-10	**0.00E+00**	**0.00E+00**	**0.00E+00**	1.08E+08	6.92E+07	**0.00E+00**	**0.00E+00**	**0.00E+00**
	STD	1.53E-06	1.23E-09	5.14E-12	**0.00E+00**	**0.00E+00**	1.63E+08	1.66E+08	5.09E-12	3.94E+07	2.74E+07
VIIC_F+CVS_N2	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	5.16E+05	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	4.66E-10	**0.00E+00**	**0.00E+00**	**0.00E+00**	6.41E+07	3.92E+07	**0.00E+00**	**0.00E+00**	**0.00E+00**
	STD	7.80E-07	8.93E-10	5.49E-12	**0.00E+00**	**0.00E+00**	2.12E+08	1.51E+08	4.54E-12	4.52E+07	7.75E+07
			F6					F15			
		Sn	Obj	G1	G2	G3	Sn	Obj	G1	G2	G3
VIIC	Best		5.03E+04	**0.00E+00**	**0.00E+00**	**0.00E+00**		1.33E+05	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median		6.46E+07	**0.00E+00**	6.70E+05	0.00E+00		2.36E+08	**0.00E+00**	8.72E+06	1.43E+07
	STD		3.20E+08	8.36E-12	7.44E+07	7.45E+07		6.73E+08	5.01E-12	8.44E+07	5.71E+07
SA1_VIIC_F+CVS	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	2.96E+06	4.88E-04	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	1.62E+08	6.10E+07	**0.00E+00**	**0.00E+00**	**0.00E+00**
	STD	5.72E+06	8.75E-06	5.94E-12	**0.00E+00**	**0.00E+00**	6.95E+08	1.06E+08	5.51E-12	9.46E+07	**0.00E+00**
SA2_VIIC_F+CVS	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	4.88E+04	3.05E-05	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	2.93E+08	9.01E+07	**0.00E+00**	**0.00E+00**	**0.00E+00**
	STD	1.57E+06	4.66E-06	7.48E-12	**0.00E+00**	**0.00E+00**	8.11E+08	9.93E+07	4.92E-12	3.90E+07	3.73E+07
VIIC_F+CVS	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	1.43E+05	1.43E+05	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	4.21E+07	4.21E+07	**0.00E+00**	**0.00E+00**	**0.00E+00**
	STD	8.79E-06	7.22E-06	8.80E-12	0.00E+00	0.00E+00	1.17E+08	9.67E+07	6.46E-12	3.33E+07	7.86E+06
VIIC_F+CVS_N1	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	6.10E-05	6.10E-05	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	5.21E+07	5.21E+07	**0.00E+00**	**0.00E+00**	**0.00E+00**
	STD	**0.00E+00**	8.73E-06	7.19E-12	**0.00E+00**	**0.00E+00**	1.98E+08	1.98E+08	3.24E-12	2.54E+06	8.67E+05
VIIC_F+CVS_N2	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	2.02E+05	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	4.77E+07	2.25E+07	**0.00E+00**	**0.00E+00**	**0.00E+00**
	STD	8.45E-06	3.38E-06	3.50E-12	**0.00E+00**	**0.00E+00**	1.43E+08	9.02E+07	5.81E-12	9.37E+07	1.13E+07
			F9					F18			
		Sn	Obj	G1	G2	G3	Sn	Obj	G1	G2	G3
VIIC	Best		**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**		4.20E+05	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median		5.86E+07	**0.00E+00**	3.82E+05	3.09E+06		2.64E+09	**0.00E+00**	1.51E+07	4.73E+06
	STD		1.91E+08	4.33E-12	1.31E+08	7.61E+07		4.56E+09	5.94E-12	1.42E+08	8.69E+07
SA1_VIIC_F+CVS	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	9.88E+07	7.86E+07	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	2.17E+09	1.39E+09	**0.00E+00**	**0.00E+00**	**0.00E+00**
	STD	4.02E+06	3.43E-06	7.52E-12	0.00E+00	0.00E+00	3.54E+09	2.51E+09	4.44E-12	7.03E+07	4.11E+07
SA2_VIIC_F+CVS	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	1.18E+06	7.77E+05	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	2.16E+09	1.33E+09	**0.00E+00**	**0.00E+00**	**0.00E+00**
	STD	1.02E+08	3.40E-06	3.47E-12	**0.00E+00**	**0.00E+00**	3.87E+09	2.51E+09	4.33E-12	3.65E+07	5.30E+07
VIIC_F+CVS	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	1.13E+07	1.13E+07	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	1.09E+09	1.03E+09	**0.00E+00**	**0.00E+00**	2.89E+07
	STD	**0.00E+00**	4.48E-06	4.96E-12	0.00E+00	0.00E+00	2.59E+09	2.54E+09	6.97E-12	6.65E+07	5.86E+07
VIIC_F+CVS_N1	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	6.12E+04	6.12E+04	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	5.78E+08	5.78E+08	**0.00E+00**	**0.00E+00**	**0.00E+00**
	STD	**0.00E+00**	3.19E-06	3.79E-12	**0.00E+00**	**0.00E+00**	3.53E+09	3.50E+09	5.92E-12	1.67E+06	6.48E+07
VIIC_F+CVS_N2	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	2.74E+06	2.74E+06	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	2.51E+09	2.36E+09	**0.00E+00**	**0.00E+00**	**0.00E+00**
	STD	1.68E-06	3.79E-06	5.51E-12	0.00E+00	0.00E+00	3.05E+09	3.04E+09	9.16E-12	3.57E+07	4.03E+07

TABLE IV
STATISTICAL RESULTS FOR DIMENSION 500

			F3					F12			
		Sn	Obj	G1	G2	G3	Sn	Obj	G1	G2	G3
VIIC	Best		**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**		2.77E+03	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median		1.49E-08	2.91E-11	2.15E+07	6.48E+06		4.39E+08	5.82E-11	9.34E+06	2.80E+06
	STD		2.54E-08	7.39E-11	1.58E+08	5.01E+07		3.36E+09	7.71E-11	1.37E+08	1.07E+08
SA1_VIIC_F+CVS	Best	**0.00E+00**	2.91E-10	**0.00E+00**	**0.00E+00**	**0.00E+00**	1.02E+06	6.71E+05	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	3.26E-08	5.82E-11	**0.00E+00**	**0.00E+00**	8.93E+08	5.18E+08	2.18E-11	1.08E+07	5.35E+06
	STD	**0.00E+00**	3.84E-08	6.67E-11	1.68E-06	**0.00E+00**	5.12E+09	3.09E+09	8.48E-11	2.07E+08	1.27E+08
SA2_VIIC_F+CVS	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	6.08E+05	4.27E+05	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	1.35E-08	5.82E-11	**0.00E+00**	**0.00E+00**	1.45E+09	8.91E+08	2.91E-11	3.94E+06	2.17E+06
	STD	**0.00E+00**	2.61E-08	7.94E-11	3.11E-06	**0.00E+00**	3.60E+09	2.38E+09	8.59E-11	1.80E+08	5.96E+07
VIIC_F+CVS	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	8.11E+05	8.11E+05	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	1.86E-08	5.82E-11	**0.00E+00**	**0.00E+00**	1.27E+09	1.20E+09	2.91E-11	3.52E+07	0.00E+00
	STD	3.11E-06	2.76E-08	6.71E-11	3.35E-06	**0.00E+00**	3.15E+09	2.96E+09	7.02E-11	2.00E+08	2.85E+07
VIIC_F+CVS_N1	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	1.63E+07	1.58E+07	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	8.38E-09	2.91E-11	0.00E+00	**0.00E+00**	2.97E+09	2.80E+09	5.82E-11	1.68E+07	1.79E+06
	STD	3.11E-06	2.71E-08	9.31E-11	1.53E-06	**0.00E+00**	3.96E+09	3.78E+09	5.30E-11	1.91E+08	1.12E+08
VIIC_F+CVS_N2	Best	**0.00E+00**	2.33E-10	**0.00E+00**	**0.00E+00**	**0.00E+00**	1.26E+07	1.15E+07	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	2.42E-08	4.37E-11	**0.00E+00**	**0.00E+00**	7.29E+08	7.09E+08	5.82E-11	9.35E+06	**0.00E+00**
	STD	**0.00E+00**	2.16E-08	6.22E-11	7.65E-07	**0.00E+00**	2.09E+09	2.00E+09	6.97E-11	8.48E+07	8.62E+07
			F6					F15			
		Sn	Obj	G1	G2	G3	Sn	Obj	G1	G2	G3
VIIC	Best		7.08E+06	**0.00E+00**	**0.00E+00**	**0.00E+00**		9.36E+04	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median		6.90E+08	4.37E-11	2.41E+07	2.41E+07		3.19E+08	7.28E-12	8.38E+06	5.73E+06
	STD		1.79E+09	7.68E-11	2.22E+08	1.46E+08		2.70E+09	4.96E-11	8.46E+07	7.17E+07
SA1_VIIC_F+CVS	Best	7.88E+06	3.64E+06	**0.00E+00**	**0.00E+00**	**0.00E+00**	1.75E+06	1.42E+06	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	5.27E+08	2.41E+08	5.82E-11	6.58E+06	**0.00E+00**	1.81E+09	1.00E+09	5.82E-11	1.68E+07	9.84E+06
	STD	1.49E+09	6.71E+08	9.46E-11	5.02E+07	4.57E+07	4.02E+09	2.67E+09	7.90E-11	1.37E+08	8.76E+07
SA2_VIIC_F+CVS	Best	2.73E+03	1.50E+03	**0.00E+00**	**0.00E+00**	**0.00E+00**	7.98E+06	5.08E+06	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	7.87E+08	3.68E+08	5.82E-11	1.02E+06	1.11E+05	1.97E+09	1.21E+09	2.91E-11	1.16E+07	1.03E+07
	STD	1.46E+09	7.69E+08	1.12E-10	1.15E+08	9.14E+07	3.77E+09	2.32E+09	6.79E-11	9.30E+07	6.70E+07
VIIC_F+CVS	Best	3.92E+04	3.52E+04	**0.00E+00**	**0.00E+00**	**0.00E+00**	2.71E+07	2.64E+07	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	2.24E+08	1.79E+08	2.91E-11	9.54E-07	3.26E+05	7.25E+08	6.80E+08	5.82E-11	1.40E+07	7.44E+06
	STD	9.68E+08	7.75E+08	8.92E-11	2.26E+08	7.01E+07	2.96E+09	2.90E+09	6.37E-11	7.03E+07	9.22E+07
VIIC_F+CVS_N1	Best	1.37E+05	1.37E+05	**0.00E+00**	**0.00E+00**	**0.00E+00**	2.29E+07	2.23E+07	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	1.99E+08	1.76E+08	1.46E-11	1.83E+06	0.00E+00	1.66E+09	1.48E+09	5.82E-11	1.88E+07	1.37E+07
	STD	7.01E+08	6.37E+08	3.54E-11	7.56E+07	3.22E+07	3.44E+09	3.17E+09	8.92E-11	1.91E+08	1.11E+08
VIIC_F+CVS_N2	Best	8.10E+04	8.10E+04	**0.00E+00**	**0.00E+00**	**0.00E+00**	7.70E+05	7.49E+05	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	1.38E+08	1.14E+08	2.91E-11	3.91E+06	**0.00E+00**	2.84E+09	2.69E+09	5.82E-11	7.68E+07	**0.00E+00**
	STD	5.16E+08	4.79E+08	6.33E-11	5.41E+07	4.84E+07	3.91E+09	3.67E+09	7.97E-11	1.85E+08	1.49E+08
			F9					F18			
		Sn	Obj	G1	G2	G3	Sn	Obj	G1	G2	G3
VIIC	Best		7.86E+06	**0.00E+00**	**0.00E+00**	**0.00E+00**		1.18E+08	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median		3.54E+08	4.37E-11	4.17E+07	3.93E+07		4.65E+09	5.82E-11	7.68E+06	6.64E+06
	STD		1.03E+09	5.67E-11	1.65E+08	1.51E+08		2.66E+10	1.18E-10	1.07E+08	1.65E+08
SA1_VIIC_F+CVS	Best	1.05E+07	2.41E+06	**0.00E+00**	**0.00E+00**	**0.00E+00**	3.38E+07	2.95E+07	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	3.30E+08	8.87E+07	5.82E-11	1.38E+07	0.00E+00	1.17E+10	9.46E+09	2.91E-11	5.97E+07	5.04E+06
	STD	1.36E+09	4.33E+08	7.66E-11	9.58E+07	1.52E+08	2.07E+10	1.79E+10	1.08E-10	1.77E+08	1.01E+08
SA2_VIIC_F+CVS	Best	1.75E+05	3.88E+04	**0.00E+00**	**0.00E+00**	**0.00E+00**	9.43E+06	8.35E+06	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	8.00E+08	2.86E+08	5.82E-11	1.91E-06	0.00E+00	2.03E+09	1.72E+09	2.91E-11	4.96E+06	1.98E+06
	STD	1.09E+09	3.12E+08	7.48E-11	1.14E+08	6.37E+07	2.56E+10	2.21E+10	6.49E-11	1.09E+08	1.55E+08
VIIC_F+CVS	Best	2.39E+05	2.39E+05	**0.00E+00**	**0.00E+00**	**0.00E+00**	5.69E+07	5.66E+07	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	4.37E+08	3.28E+08	5.82E-11	**0.00E+00**	**0.00E+00**	1.23E+10	1.22E+10	2.91E-11	2.80E+07	2.44E+05
	STD	3.87E+08	3.33E+08	9.10E-11	6.51E+07	8.65E+07	2.15E+10	2.14E+10	1.11E-10	1.63E+08	8.48E+07
VIIC_F+CVS_N1	Best	8.05E+04	6.44E+04	**0.00E+00**	**0.00E+00**	**0.00E+00**	3.35E+06	3.29E+06	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	1.45E+08	1.28E+08	2.91E-11	3.24E+06	**0.00E+00**	1.97E+10	1.96E+10	5.82E-11	1.13E+07	**0.00E+00**
	STD	3.51E+08	3.49E+08	6.69E-11	3.98E+07	1.74E+07	2.42E+10	2.40E+10	1.19E-10	1.73E+08	1.37E+08
VIIC_F+CVS_N2	Best	8.20E+05	4.62E+05	**0.00E+00**	**0.00E+00**	**0.00E+00**	1.26E+06	1.25E+06	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	8.58E+07	6.87E+07	2.91E-11	3.51E+06	**0.00E+00**	7.95E+09	7.89E+09	1.46E-11	1.19E+07	1.92E+06
	STD	3.42E+08	1.65E+08	6.19E-11	9.26E+07	1.27E+08	1.86E+10	1.84E+10	6.88E-11	1.70E+08	8.93E+07

TABLE V
STATISTICAL RESULTS FOR DIMENSION 1000

			F3					F12			
		Sn	Obj	G1	G2	G3	Sn	Obj	G1	G2	G3
VIIC	Best		**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**		2.99E+06	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median		4.84E-08	**5.82E-11**	6.49E+07	3.77E+07		3.03E+09	1.75E-10	4.57E+07	3.48E+07
	STD		9.54E-08	2.89E-10	1.72E+08	1.07E+08		8.40E+09	**3.78E-10**	3.01E+08	1.76E+08
SA1_VIIC_F+CVS	Best	**0.00E+00**	4.66E-10	**0.00E+00**	**0.00E+00**	**0.00E+00**	3.04E+05	2.28E+05	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	5.96E-08	1.16E-10	**0.00E+00**	**0.00E+00**	**1.25E+09**	**1.04E+09**	1.16E-10	5.08E+07	**8.25E+06**
	STD	3.95E+06	1.05E-07	2.92E-10	3.05E-06	**8.35E-07**	8.45E+09	6.31E+09	3.61E-10	2.05E+08	9.35E+07
SA2_VIIC_F+CVS	Best	**0.00E+00**	1.40E-09	**0.00E+00**	**0.00E+00**	**0.00E+00**	2.04E+06	1.99E+06	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	6.33E-08	3.49E-10	**0.00E+00**	**0.00E+00**	5.02E+09	3.80E+09	1.16E-10	6.11E+07	2.49E+07
	STD	1.66E+08	1.22E-07	3.23E-10	4.53E-06	3.82E-06	1.11E+10	8.73E+09	3.17E-10	2.33E+08	1.66E+08
VIIC_F+CVS	Best	**0.00E+00**	6.98E-10	**0.00E+00**	**0.00E+00**	**0.00E+00**	5.99E+03	5.65E+03	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	1.12E-07	1.75E-10	**0.00E+00**	**0.00E+00**	3.63E+09	3.59E+09	1.75E-10	4.33E+07	2.90E+07
	STD	6.71E-06	1.38E-07	3.61E-10	4.40E-06	2.20E-06	9.42E+09	9.11E+09	3.24E-10	2.17E+08	1.34E+08
VIIC_F+CVS_N1	Best	**0.00E+00**	5.59E-09	**0.00E+00**	**0.00E+00**	**0.00E+00**	1.50E+07	1.46E+07	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	4.47E-08	1.75E-10	**0.00E+00**	**0.00E+00**	1.37E+09	1.35E+09	2.04E-10	1.78E+07	1.37E+07
	STD	3.06E-06	8.71E-08	3.44E-10	4.41E-06	1.72E-06	7.48E+09	7.11E+09	2.16E-10	3.08E+08	1.30E+08
VIIC_F+CVS_N2	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	3.73E+05	3.60E+05	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**0.00E+00**	7.64E-08	2.33E-10	**0.00E+00**	**0.00E+00**	3.11E+09	3.00E+09	2.33E-10	5.34E+07	1.07E+07
	STD	1.53E-06	**1.29E-07**	**4.48E-10**	5.15E-06	1.58E-06	**6.21E+09**	**6.04E+09**	2.21E-10	**1.60E+08**	**8.15E+07**
			F6					F15			
		Sn	Obj	G1	G2	G3	Sn	Obj	G1	G2	G3
VIIC	Best		6.70E+06	**0.00E+00**	**0.00E+00**	**0.00E+00**		4.23E+07	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median		2.00E+09	1.16E-10	1.26E+08	3.99E+07		1.97E+09	1.16E-10	5.21E+07	4.44E+07
	STD		3.55E+09	3.49E-10	3.42E+08	1.98E+08		9.57E+09	2.61E-10	2.15E+08	1.95E+08
SA1_VIIC_F+CVS	Best	**4.12E+04**	**2.32E+04**	**0.00E+00**	**0.00E+00**	**0.00E+00**	3.01E+07	2.28E+07	**0.00E+00**	8.45E+05	**0.00E+00**
	Median	**3.67E+08**	**1.93E+08**	1.16E-10	**1.11E+07**	4.65E+06	2.68E+09	1.90E+09	2.33E-10	8.71E+07	4.14E+07
	STD	2.58E+09	1.72E+09	2.20E-10	**1.49E+08**	9.87E+07	1.15E+10	8.78E+09	**3.64E-10**	2.48E+08	1.75E+08
SA2_VIIC_F+CVS	Best	1.21E+06	7.44E+05	**0.00E+00**	**0.00E+00**	**0.00E+00**	**9.87E+05**	**7.80E+05**	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	2.01E+09	1.38E+09	**5.82E-11**	8.45E+07	6.65E+07	3.02E+09	2.52E+09	2.33E-10	5.54E+07	2.77E+07
	STD	3.62E+09	1.95E+09	**3.83E-10**	2.51E+08	1.11E+08	9.01E+09	7.07E+09	3.46E-10	1.89E+08	1.32E+08
VIIC_F+CVS	Best	4.19E+06	4.02E+06	**0.00E+00**	**0.00E+00**	**0.00E+00**	2.39E+07	**2.34E+07**	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	1.63E+09	1.30E+09	2.33E-10	1.01E+08	1.31E+07	2.40E+09	2.24E+09	1.16E-10	4.37E+07	1.12E+07
	STD	2.52E+09	2.37E+09	3.21E-10	1.67E+08	1.11E+08	6.36E+09	6.11E+09	2.03E-10	1.97E+08	9.19E+07
VIIC_F+CVS_N1	Best	5.14E+06	4.28E+06	**0.00E+00**	**0.00E+00**	**0.00E+00**	1.13E+07	1.06E+07	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	9.54E+08	8.62E+08	1.16E-10	2.80E+07	**0.00E+00**	9.32E+08	**9.12E+08**	**8.73E-11**	**1.83E+07**	1.83E+07
	STD	**1.92E+09**	**1.60E+09**	2.52E-10	2.76E+08	9.16E+07	7.07E+09	6.83E+09	2.83E-10	1.72E+08	9.39E+07
VIIC_F+CVS_N2	Best	4.97E+05	4.97E+05	**0.00E+00**	**0.00E+00**	**0.00E+00**	1.11E+08	1.04E+08	**0.00E+00**	4.98E+06	**0.00E+00**
	Median	7.58E+08	6.32E+08	1.75E-10	4.00E+07	4.30E+04	**2.14E+09**	2.02E+09	1.16E-10	5.92E+07	**1.10E+07**
	STD	2.19E+09	2.02E+09	2.65E-10	1.60E+08	**7.94E+07**	**5.45E+09**	**5.32E+09**	3.50E-10	**1.04E+08**	**7.32E+07**
			F9					F18			
		Sn	Obj	G1	G2	G3	Sn	Obj	G1	G2	G3
VIIC	Best		3.65E+06	**0.00E+00**	**0.00E+00**	**0.00E+00**		3.97E+08	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median		7.48E+08	2.33E-10	5.30E+07	7.10E+07		1.63E+10	**2.33E-10**	4.62E+07	3.41E+07
	STD		1.76E+09	3.88E-10	2.67E+08	1.82E+08		4.37E+10	**3.92E-10**	2.21E+08	1.13E+08
SA1_VIIC_F+CVS	Best	1.36E+06	5.71E+05	**0.00E+00**	**0.00E+00**	**0.00E+00**	1.59E+08	1.38E+08	**0.00E+00**	5.76E+05	**0.00E+00**
	Median	1.51E+09	7.54E+08	2.33E-10	4.84E+07	**7.63E-06**	7.49E+09	**6.63E+09**	1.16E-10	**3.67E+07**	2.69E+07
	STD	2.23E+09	1.16E+09	3.55E-10	2.00E+08	1.30E+08	3.39E+10	3.05E+10	2.32E-10	**1.61E+08**	1.28E+08
SA2_VIIC_F+CVS	Best	1.26E+05	5.27E+04	**0.00E+00**	**0.00E+00**	**0.00E+00**	**2.98E+05**	**2.66E+05**	**0.00E+00**	4.66E-10	**0.00E+00**
	Median	6.72E+08	3.31E+08	1.16E-10	1.17E+07	1.05E+04	2.23E+10	2.03E+10	2.33E-10	1.06E+08	3.74E+07
	STD	2.40E+09	1.32E+09	**4.89E-10**	2.28E+08	3.92E+07	3.98E+10	3.66E+10	3.75E-10	1.65E+08	1.03E+08
VIIC_F+CVS	Best	1.61E+06	1.61E+06	**0.00E+00**	**0.00E+00**	**0.00E+00**	1.38E+07	1.37E+07	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	7.92E+08	6.93E+08	2.04E-10	4.94E+07	1.87E+07	1.18E+10	1.17E+10	2.33E-10	4.32E+07	2.40E+07
	STD	1.30E+09	1.01E+09	3.30E-10	2.34E+08	1.70E+08	4.26E+10	4.23E+10	2.88E-10	2.38E+08	1.61E+08
VIIC_F+CVS_N1	Best	3.43E+05	2.74E+05	**0.00E+00**	**0.00E+00**	**0.00E+00**	8.55E+06	8.52E+06	**0.00E+00**	1.74E+04	**0.00E+00**
	Median	3.73E+08	2.80E+08	2.33E-10	2.48E+07	3.81E-06	1.38E+10	1.37E+10	1.16E-10	5.67E+07	1.68E+07
	STD	1.23E+09	1.08E+09	2.10E-10	1.63E+08	3.21E+07	3.84E+10	3.80E+10	3.54E-10	1.74E+08	2.08E+08
VIIC_F+CVS_N2	Best	**1.86E+03**	**1.72E+03**	**0.00E+00**	**0.00E+00**	**0.00E+00**	5.55E+06	5.50E+06	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Median	**3.02E+08**	**2.82E+08**	1.16E-10	**1.01E+07**	1.63E+06	**7.08E+09**	7.01E+09	1.75E-10	4.15E+07	**8.18E+06**
	STD	**8.76E+08**	**7.61E+08**	1.82E-10	**8.49E+07**	8.93E+07	**2.56E+10**	**2.54E+10**	1.42E-10	8.58E+07	**1.01E+08**