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ANALYSIS OF PROJECT DURATION: UNCERTAINTY USING GLOBAL SENSITIVITY ANALYSIS

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ABSTRACT

Estimating the duration of a project is important in project management. The dependency structure matrix has been used to estimate the duration of projects, and it has proven to be useful especially in complex projects, for example project with activity overlapping. This estimate is based on the duration of the activities, their interrelationships and the permitted level of overlap. However, these variables have uncertainty that generate uncertainty in the duration of the project. The methods of global sensitivity analysis Morris and Sobol' are used in this study to identify the key activities that affect the uncertainty in the duration of the project. It is shown that adequate control of the uncertainty in these activities significantly reduces the uncertainty in the duration of the project. Examples with and without overlapping are used to explain the methodologies.

INTRODUCTION

The sequence of tasks is vital to the development of any project. Good sequencing reduces the amount of time necessary for completion. The order of tasks is influenced by the information flow among them. The dependency structure matrix *(DSM)* can be used to model information flow in complex projects, e.g. project with overlap. However, the information used by the DSM, including task duration, time required for communication, and task overlap, can have uncertain values. However, there is no methodology for the identification of significant and insignificant input factors on the project duration uncertainty. The aim of this paper is to show that global sensitivity analysis *(GSA)* can be used to identify significant and insignificant input factors on the project duration using the DSM.

The DSM is a widely used tool because it allows the different parts of the project or product to be broken down or to be put together. The complexity is simplified by breaking down the project into smaller tasks, identifying the relationship between them, assessing their impact on the project, and assigning resources to individual tasks *(Browning, 2001)*.

Moreover, the scheduling of projects is based on finding resources and scheduling activities with the goal of optimizing the efficiency of the project *(Tienda et al., 2011)*. Overlapping of sequential activities occurs on most projects *(Srour et al, 2013)*, which requires a two-way exchange of information among dependent design disciplines. That is, there are interdependent tasks and loops. As a result of the factors previously mentioned, recent efforts to reconcile project scheduling and DSM have sought to produce a tool that serves two purposes: analysis and project scheduling *(Maheswari and Varghese, 2005; Srour et al., 2013)*. Researchers have demonstrated that DSM is a powerful tool in planning the sequence of tasks.

However, tasks in a project are subject to many unknown factors *(Herroelen and Leus 2005; Perminova et al. 2007)* that can lead to changes in scheduling. These uncertainty-causing factors include: tasks taking more or less time than was originally estimated, resources not being available, required materials being ready before they are scheduled to arrive, tasks being introduced or withdrawn, and weather conditions. These changes or uncertainties can cause the schedule to be delayed, increase stock, or require major work, all of which lead to higher costs than those originally planned.

One of the limitations of the research conducted by Maheswari and Varghese is the difficulty of obtaining a well-founded estimate of how long each task, the communication among tasks, and the overlap of tasks will take. Gálvez et al. *(2012)* studied the effect of uncertainty of task programming using DSM and grey theory or interval arithmetic. Shi and Blomquist *(2012)* extended the DSM method proposed by Maheswari and Varghese *(2005)* using fuzzy numbers. Recently, Galvez et al. *(2015)* studied the uncertainty of project duration using Monte Carlo simulation and DSM. These studies are related to uncertainty analysis.

Uncertainty analysis refers to the determination of the uncertainty in output results that derives from uncertainty in input factors *(Helton et al., 2006)*. Therefore, the previous works are related to the characterization of uncertainty *(grey number in the work of Gálvez et al. (2015)*, fuzzy numbers in the work of Shi and Blomquist *(2012)*, and distribution functions in Gálvez et al., *(2015)*) and presentation of uncertainty output results. However, no work has performed sensitivity analysis.

Sensitivity analysis refers to the determination of the contribution of individual uncertainty inputs to the uncertainty in output results *(Helton et al. 2006)*. According to Saltelli et al. *(2008)*, the GSA can be defined as "the study of how uncertainty in the output of a model *(numerical or otherwise)* can be apportioned to different sources of uncertainty in the model input". These techniques have been widely used in different engineering areas and are of great importance to know the most significant variables in a model. The general objectives of GSA are: a) Identification of significant and insignificant factors. Possible reduction of the dimensions *(number of design variables)* of the optimization problem, b) Improvement in understanding the model behavior *(highlight interactions among factors, find combinations of factors that result in high or low values for the model output)*. GSA corresponds to the evaluation of an output model when all model factors are simultaneously evaluated, being mainly resolved by numerical methods. This methodology has the advantage of simultaneously assessing all factors, while its disadvantage is that it requires a large number of data for which the model is evaluated and mathematical techniques are more complex. GSA methods can be classified into three groups *(Confalonieri et al., 2010)*: 1) Regression methods, 2) Screening methods, and 3) Variance –based methods. Screening methods proceed from the area of experimental design and usually applied to problems that involve from a few input factors to a few tens. Examples of these methods are fractional factorial design, Morris method and sequential bifurcation. In variance-based method, the variance of the model output can be decomposed into terms of increasing dimension, called partial variances, which represent the contribution of the inputs *(i.e., single inputs, pairs of inputs, etc.)* to the overall uncertainty in the model output. Statistical estimators of partial variances are available to quantify the sensitivities of all the inputs and of groups of inputs through multi-dimensional integrals. To preclude a high computation cost, Homma and Saltelli *(1996)*

*Paper approved for 2nd International Conference in Project Management at UQTR (May, 2015) introduced the concept of a total sensitivity index. The total sensitivity index indicates the overall effect of a given input, by considering all the possible interactions of the respective input with all the other inputs. Some techniques in this group are: the Fourier amplitude sensitivity test *(FAST)*, extended Fourier amplitude sensitivity test *(E-FAST)*, Sobol' method, and high dimensional model representation *(HDMR)*.

In this paper the Morris and Sobol' methods are applied to project planning using the DSM. Through an example it is demonstrated that GSA can identify input factors that most affect the duration of the project. Then, with proper management of these input factors, the uncertainty in the project duration can be significantly reduced. An example, with and without overlapping is analyzed.

1. Strategy Used

In this work an example is used to explain how the GSA can be used to identify the activities uncertainty that most affect the uncertainty on the project duration. The GSA methods used are Sobol' and Morris methods. Then, in this section an example is introduced and a brief description of Sobol' and Morris methods are given and applied to the example.

Example without overlap

The example consists of six activities from A to F, and the DSM representation of the example is given in figure 1. The DSM is a square matrix containing a list of activities in the rows and columns in the same order. The order of activities in the rows and columns in the matrix indicates the sequence of execution *(for more information see Maheswari and Varghese, 2005)*. Values in the diagonal are the mean duration of the activities *(days)*, for example the mean duration of activity A is 2 days. A value in the off-diagonal cells indicated that these activities are information predecessors. This means that activity B needs information from activity A and activity D needs information from activities B and C. The values in the off-diagonal cells will be used later when overlapping is included in the example.

Based on the mean values of the activities the conventional project duration is estimated in 14 days (**Figure 2**). Note that activity C has not effect on the project duration and all other activities are in the sequence of execution without any time leftover between activities. The conventional project duration is estimated with,

$$(EF)_i = (ES)_i + A_{ii} \qquad 0 < i \le n \tag{1}$$

$$(ES)_j = \mathrm{Max}[(EF)_i] \qquad 0 < i \le n,\ 0 < j \le n \tag{2}$$

$$\text{Conventional project duration} = \mathrm{Max}[(EF)_j]\ 0 < j \le n \tag{3}$$

Where *n* is the number of activities; *i* all the immediate predecessors of *j*; *j* the current activity chosen in the order as identified by DSM; *ES* the early start; *EF* the early finish; and A_{ii} the diagonal values of the DSM *(duration of activity)*.

Let us assume that each duration activity has uncertainty of ±0.5 days with uniform distribution. Then, for example activities A and D have a duration of ~Unif*(1.5,2.5)* and ~Unif*(4.5,5.5)* respectively. Two questions arise 1) what is the uncertainty in the project duration given the uncertainty in the activity durations, and 2) how important are the activity durations with respect to the uncertainty in the project duration. The goal of uncertainty analysis is to answer the first question, and the goal of sensitivity analysis is to answer the second question *(Helton et al., 2006)*.

Global Sensitivity Analysis

GSA methods enable studying how the uncertainty in the output of a model can be assigned to different sources of uncertainty in the model input when all model inputs are simultaneously evaluated. In our case, GSA methods will be used to study how the uncertainty in the project duration can be assigned to the activity duration and overlapping factor uncertainties. Two method are used: Morris and Sobol' methods.

The Morris *(1991)* method is based on a discretization of the inputs in levels allowing a fast exploration of the model behavior. The aim of this method is to identify the non-influential inputs with a small number of model calls. The Morris method allows classifying the inputs into inputs that have negligible effects, input having large linear effects without interactions, and inputs having large non-linear and/or interaction effects. The method consists in random One-At a Time *(OAT)* design of experiments with random direction of the variation. The repetition of these steps allows estimating the elementary effects for each input and the consequent calculation of sensitivity indices.

The Morris sensitivity indices are the mean of the absolute value of the elementary effects *(μ^*_j)* and the standard deviation of the elementary effects *(σ_j)*. The μ^*_j is a measure of influence of the j-th input on the output; if μ^*_j is zero the effect of the j-th input is negligible, and the larger the μ^*_j value the more the j-th input contributes to the uncertainty of the output. The σ_j is a measure of the non-linear and/or interaction effects of the j-th input. If σ_j is zero then the elementary effects have no variations on the support of the input. Usually a graph of σ_j versus μ^*_j is used because it allows to distinguish three group: low values of μ^*_j *(inputs that have negligible effect on the output)*, large values of μ^*_j and low values of σ_j *(inputs that have linear effects without interaction)*, and large values of both μ^*_j and σ_j *(inputs that have non-linear effects and/or interaction)*.

The Morris method was applied to the example *(Eqs, 1 to 3)* using 15 OAT experiments which require 105 model calls. The software R *(R Core Team, 2013)*, package sensitivity *(Pujol et al., 2014)*, which is a free software environment for statistical computing and graphics was used. **Figure 3** plots the results. It is easy to visualize that A, B, D, E and F activities are influential *(large values of μ^*_j)*, while C has no effects *(values of μ^*_j close to zero)*. In addition A and F have linear effects without interaction *(values of σ_j equal to zero)*, and D and E have non-linear effects and/or interaction *(large values of both μ^*_j and σ_j)*.

The Sobol' method is based on the partitioning of the total variance of model output V(Y), considering that the model has the form Y = f(x_1, x_2, ...

	A	B	C	D	E	F
A	2					
B	0.87	4				
C	0.95		3.5			
D		0.95	0.95	5		
E		0.95			5	
F				0.95	0.95	3

Time factor of processor activities (B_{ij})

	A	B	C	D	E	F
A	2					
B	0.13	4				
C	0.05		3.5			
D		0.05	0.05	5		
E		0.05			5	
F				0.05	0.05	3

Time factor of receiving information (C_{ij})

FIGURE 1. *DSM showing the mean values of duration of activities and time factor of transfer of information between activities.*

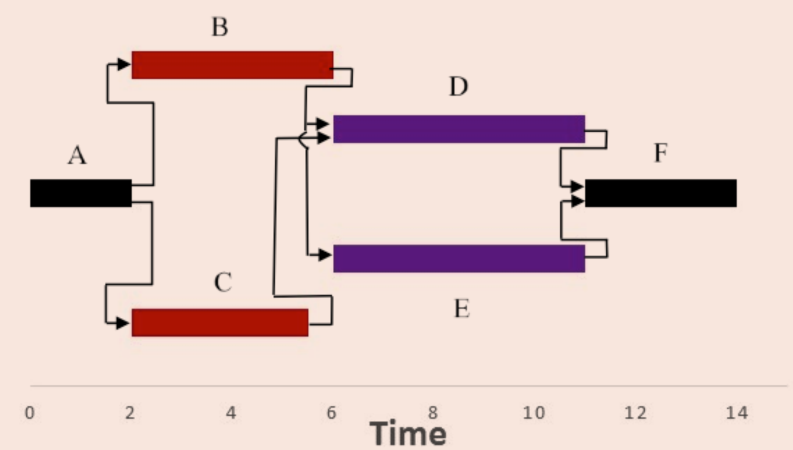


FIGURE 2. *Estimation and representation of conventional project duration.*

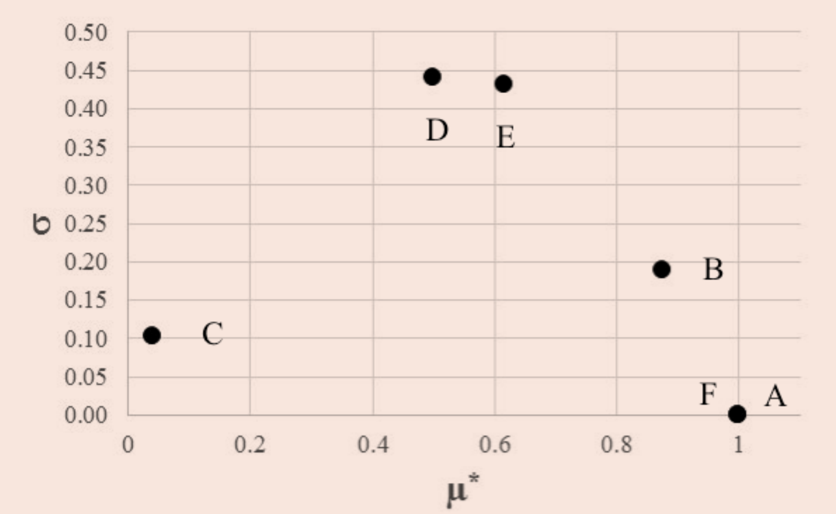


FIGURE 3. *Results of Morris method with 15 OAT experiments for example without overlap.*

x_n), where Y is a scalar and x_i is a model factor, using the following equation *(Confalonieri et al., 2010)*:

$$V(Y) = \sum_{i=1}^{n} D_i + \sum_{i \le j \le n}^{n} D_{ij} + \cdots + \sum_{i \le \ldots n}^{n} D_{i \ldots n} \quad (4)$$

Where D_i represent the first order effect for each factor x_i($Di=V[E(Y|x_i)]$) and D_{ij}($D_{ij} = V[E(Y|x_i,x_j)] - D_i - D_j$) to $D_{1\ldots n}$ the interactions among n factors. The variance of the conditional expectation ($V[E(Y|x_i)]$) is sometimes called main effect and used as an indicator of the significance of x_i. The Sobol' method allows calculating two indices, i.e., the first order effect sensitivity index corresponding to a single factor (x_i):

$$S_i = \frac{V[E(Y|x_i)]}{V(Y)} \quad (5)$$

and the total sensitivity index corresponding to a single factor *(index i)* and the interaction of more factors that involve the index i and at least one index j ≠ i from 1 to n

$$ST_i = \sum_i S_i + \sum_{j \ne i} S_{ij} + \cdots + S_{1,\ldots,n} \quad (6)$$

The first order sensitivity index measures only the main effect contribution of each input factor on the output variance. It does not take into account the interactions among factors. The first-order sensitivity index (S_i) is important when the objective is to determine the most important input uncertainties. The total sensitivity index (ST_i) is important when the objective is to reduce the uncertainty in the output model (*Adeyinka, 2007*). If the first-order sensitivity index (S_i) of the *i* input factor is very small, then the uncertainty in x_i does not affect the uncertainty in the output model, . Therefore, x_i is non-influential or unimportant. This does not say anything about input interactions or high-order sensitivity índices like $S_{i,j}$ or $S_{i,j,k}$. If the total sensitivity index (ST_i) is also small, then apart from being unimportant, x_i does not interact with other factors (high-order effects of x_i are negligible). The implication of small S_i and ST_i, is that the uncertainty in x_i has no affect on the uncertainty in Y. Then, in a subsequent analysis, x_i can be fixed to its nominal value (mean or median) and further research, measurement, analysis and data gathering can be directed to other factors. Conversely, regardless of the magnitude of ST_i, a large value of the first-order sensitivity index, S_i, implies that x_i is influential. The arithmetic difference between ST_i and S_i indicates the magnitude of the interactions between x_i and other factors.

Sobol' method was applied to the example (Eqs, 1 to 3) with six random inputs with Monte Carlo sampling, it has a cost of 400,000 model calls and we repeat the estimation process 100 times. The software R (R Core Team, 2013) was used with the Sobol-Jansen version in package sensitivity (Pujol et al., 2014). Figure 4 plots the results. It is easy to visualize that A, F, B, D, and E activities are influential in that order (large values of both first order and total Sobol´ indices), while C has no effects. In addition D and E have interaction (total and first order indices have different values). The interaction in other activities are small. These results are in agreement with the Morris method results.

Example with overlap

Let us consider overlap between activities. The overlap is represented in DSM in the form of ratios called time factors *(Maheswari and Varghese, 2005)*. Two times factors are used, the time factor for receiving the information for the successor activity *(represented by matrix B_{ij}, given by the off-diagonal cell in* **Figure 1***a)*, and the time factor for sending the information from predecessor activity *(represented by matrix C_{ij}, given by the off-diagonal cell in* **Figure 1***b)*. For example, 0.95 in B_{CA} implies that A can send the required information through C at the end of 0.95 times its duration, and 0.05 in C_{CA} implies that it is essential that to continue, C receives information from A, but only at 0.05 of the time of its duration, instead of at the beginning of the task.

The natural overlap project duration is estimated with,

$$(ES)_j = Max[(ES)_i + B_{ji} B_{ii} - C_{ji} C_{jj}] \qquad 0 < i \le n, 0 < j \le n \quad (7)$$

$$(EF)_i = (ES)_i + B_{ii} \qquad 0 < i \le n \quad (8)$$

$$natural\ overlap\ project\ duration = Max[(EF)_j] \qquad 0 < j \le n \quad (9)$$

Where *n* is the number of activities; *i* all the immediate predecessors of *j*; *j* the current activity chosen in the order as identified by DSM; *ES* the early start; and *EF* the early finish. Note that B_{ii} and C_{ii} are the diagonal values of the DSM *(duration of activity)*.

Based on the mean values of the activity durations and mean values of the factor time the natural overlap project duration is estimated at 12.4 days *(***Figure 5***)*. Now, let us consider that each time factor has uncertainty of ±0.05 with uniform distribution, then the off-diagonal values of B_{ij} are ~Unif*(0.9,1.0)* and the off-diagonal values of C_{ij} are ~Unif*(0.0,0.1)*, but B_{BA} ~Unif*(0.74,1.0)* and C_{BA} ~Unif*(0.0,0.26)*. Also uncertainty in the activity durations is included.

The Morris method was applied to the example with overlap *(Eqs, 7 to 9)* using 80 OAT experiments which require 1,680 model calls. **Figure 6** plots the results. It is easy to visualize that A, B, D, F activity durations and C_{BA} time factor are very influential *(large values of μ*j)*, while C, E activity durations and B_{BA}, B_{FD} time factors are influential. Also, there are interactions and/or non-linear effects in several input factors *(large values of both μ*j and sj)*.

Sobol' method was applied to the example with overlap *(Eqs, 7 to 9)* with 20 random inputs with Monte Carlo sampling, it has a cost of 1,100,000 model calls and we repeat the estimation process 100 times. **Figure 7** plots the results. It is easy to visualize that A, B, D, F activity durations and C_{BA} time factor are very influential *(large values of Sobol' indices)*, while C, E activity durations and B_{BA}, B_{FD} time factors are influential. Several time factors have no effects *(values of Sobol' indices close to zero)*. In addition B, C, D, E and C_{BA} have interaction *(Total and first order indices have different values)*.

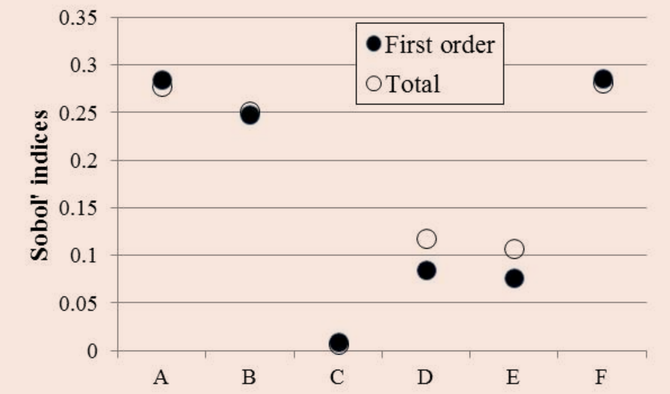


FIGURE 4. *Estimation of Sobol' indices for the example without overlap*

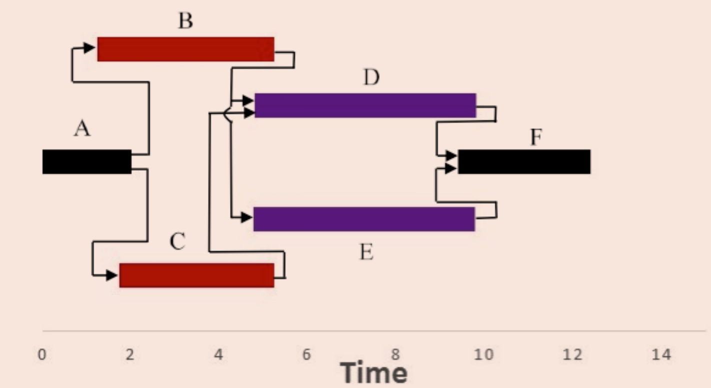


FIGURE 5. *Estimation and representation of natural overlap project duration*

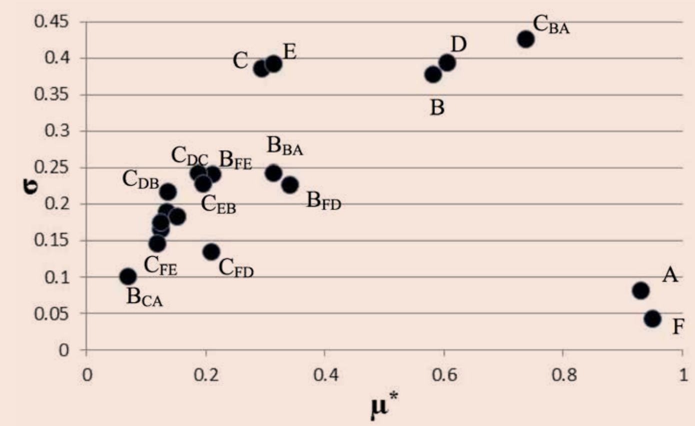


FIGURE 6. *Results of the Morris method with 80 OAT experiments for example with overlap*

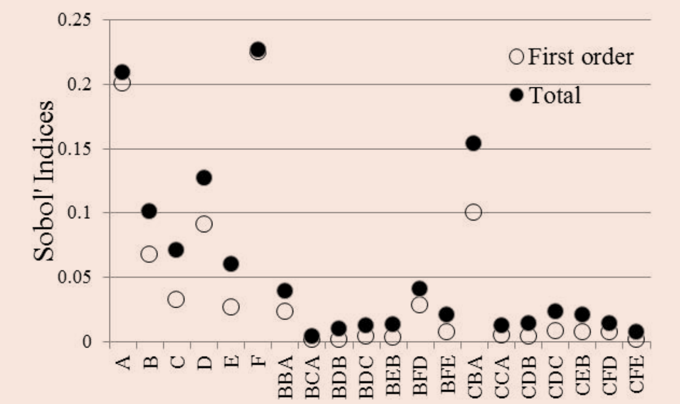


FIGURE 7. *Estimation of Sobol' indices for example with overlap*

2. Discussion

For the example without overlap all activities have the same level of uncertainty in duration, ±0.5 days, however the effect of these uncertainties on the uncertainty of the project duration is different. The uncertainty in the time duration of activities A and F are the most relevant to the uncertainty in project duration *(largest values of μ*j in Morris method and largest values of Sobol' indices)*. This is because these activities are sequential without interaction and they will always influence project implementation. The uncertainty in the time duration of activities D and E also affect the uncertainty in project duration. However, activity D will affect if the duration of activity D is greater than the duration of activity E, and vice versa. For that reason these activities have interaction *(different values in first order and total Sobol' indices)*. In Morris indices, both D and E activities have interaction and / or non-linear effects, however the model is linear *(Eq. 1-3)*, then it must be interpreted as interactions.

These results are independent of whether the Morris or Sobol' method is used. Sobol' method requires a significantly greater number of model calls than the Morris method. However, as the mathematical model is simple using the Sobol' method is not very costly from the computing point of view. Sobol' method is more robust in the presence of non-linearity and interaction among the activities because it explores the complete parameter space. Moreover, Morris method is easier to implement.

These results indicate that efforts to reduce the uncertainty in the project duration should focus on reducing uncertainty in the duration of activities A, F and B. Reducing uncertainty in the duration of activities D and E have a lower impact on the uncertainty in the project duration. Reducing uncertainty in the duration of activity C will have minimal impact. If the resources are limited, the resources must be allocated to estimate the uncertainty of activities A, F and B.

Table 1 shows the results of Monte Carlo simulations for various scenarios with 1,000 calls to the model. The second column shows the results in the project duration when considering uncertainty in all activities. Columns two, three and four show the results when *(in its average value)* the dura-

	Project duration			
	No activity fixed	**A and F fixed**	**D and E fixed**	**C fixed**
Minimum	12.41	13.15	12.74	12.53
1st Quartile	13.76	13.97	13.67	13.80
Median	14,16	14.19	14.03	14.20
Mean	14.16	14.19	14.02	14.19
3rd Quartile	14.52	14.47	14.39	14.59
Maximum	15.82	14.97	15.43	15.83

TABLE 1. *Uncertainty analysis in project duration for various scenarios.*

tion of activities A and F, D and E, and C is fixed, respectively.

Although the uncertainty in the duration of each activity has uniform distribution, the project duration is normally distributed. This was observed by Gálvez et al. *(2015)* and confirmed in the results observed in this example. Note that the average value of project duration is larger than the value calculated with the mean values *(14 days)*, because the interaction was not considered. In fact if the activity duration with the largest interaction are fixed *(D and E)* the mean value is close to the 14 days.

If all activities are uncertain then the uncertainty in the project duration is 3.4 days, if the uncertainty in activity C is removed, the uncertainty in the project duration is not significantly reduced, 3.3 days. However, if the uncertainty in the activities A and F are eliminated the uncertainty in the project duration is reduced to 1.8 days, compared with 2.7 days if the uncertainty is removed in activities D and E. This confirm that GSA can be used to reduce the uncertainty in project duration.

The final decision on where to focus efforts in reducing the uncertainty depend on these results and on other aspects such as the associated cost, availability of resources and the feasibility of reducing the uncertainty in the activity duration.

In the example with overlap it is observed that in general the time factors have less effect on the uncertainty in the project duration, with the exception of the time factor C_{BA}. This is not surprising because it is the time factor with most uncertainty. However, the effect of the B_{BA} time factor is not as significant despite having high uncertainty. This is because the effect of C_{BA} depends on the duration of activity B, whereas the effect of B_{BA} depends on the duration of activity A *(see equation 7)*, and because the duration of B is larger than the duration of activity A its effect increases.

If all activity durations and time factors have uncertainties, the uncertainty in the project duration is 4.1 days *(based on Monte Carlo simulations)*, if the input factors that most affect the project duration uncertainty are fixed at their mean value *(activities A, F, B, D, and time factor C_{BA})* the project duration uncertainty is reduced to 2.0 days. This effect is significant. If the duration of activities C and E is fixed then the project duration uncertainty is 4.0 days, i.e. its effect is marginal. On the other hand, if the duration of activities A and F is fixed the uncertainty is 3.0 days, i.e. there is a significant effect. These simulations confirm that using the methods of Morris and Sobol' allow to identify input factors that affect the uncertainty in the duration of the project and the control of uncertainty of these input factors allow to diminish the uncertainty in project duration.

The Monte Carlo simulation when all activity durations and time factors have uncertainties gives a mean value for the project duration of 12.75 days, which is different from the value when the average value of the input factors are used *(12.4 days)*. This is explained because when deterministic values are used the interaction between input factors are not considered.

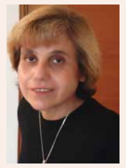
3. Conclusion

We have proposed using the Morris and Sobol' methods in order to identify the input factor uncertainty which is responsible for the uncertainty in project duration. The DSM-based scheduling proposed by Maheswari and Varghese *(2005)* was used to model de project duration based on the duration of the activities and the time factor associated to activity overlapping. It was demonstrated that both methods can be used for this purpose, however the Sobol´ method has shown to be more adequate in the ranking of the input factors and the Morris method has shown to be more adequate for screening of input factors. It was demonstrated that the control or reduction in the uncertainty of the key activity duration can reduce the uncertainty in the project duration.

It is clear that for complex projects the problem of project scheduling is far more extensive than just the duration of activities, it is also related to the issue of organizational structure, resource allocation and behaviors of stakeholders. Then, the identification of the key activities from the point of view of project duration can help to reduce the number of variables and simplify the schedule problem.

If the resources are limited, approximate uncertainty can be assigned to the duration of activity and time factor. After the key input factors are identified the resources can be allocated to estimate the uncertainty of the key input factors.

authors



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references

Adeyinka A.L., *(2007).* Applications of Sensitivity Analysis in Petroleum Engineering, Thesis University of Texas at Austin.

Browning, T.R. *(2001).* Applying the design structure matrix to system decomposition and integration problems: A review and new directions. IEEE Transactions on Engineering management, 48 *(3)*, 292-306.

Confalonieri R., Bellocchi G., Bregaglio S., Donatelli M., & Acutis M., *(2010).* Comparison of sensitivity analysis techniques: a case study with the rice model WARM, Ecological Modelling, 221, 1897 -1906.

Gálvez E.D., S.F. Capuz-Rizo, & J.B. Ordieres, *(2012).* Study of the uncertainty of task programming using the dependency structure matrix, Información Tecnológica, 23*(1)*, 19-34.

Gálvez, E.D., Ordieres, J.B., & Capuz-Rizo, S.F., *(2015).* Evaluation of Project Duration Uncertainty using the Dependency Structure Matrix and Monte Carlo Simulation, Revista de la Construcción, submitted.

Herroelen W., & R. Leus, *(2005).* Project scheduling under uncertainty: survey and research potentials, European J. of operational research, 165, 289-306.

Homma T., & Saltelli A., *(1996).* Importance measures in global sensitivity analysis of nonlinear models, Reliability Engineering & System Safety, 52, 1-17.

Helton, J.C., Johnson, J.D., Sallaberry, C.J., & Storlie, C.B., *(2006).* Survey of sampling-based methods for uncertainty and sensitivity analysis, Reliability Engineering & System Safety, 91, 1175-1209.

Maheswari J.U., & K. Varghese, *(2005).* Project scheduling using dependency structure matrix, International Journal of Project Management, 23 *(3)*, 223-230.

Morris M.D., *(1991).* Factorial sampling plans for preliminary computational experiments, Technometrics, 33, 161-174.

Perminova O., M. Gustafsson, & K. Wikström, *(2007).* Defining uncertainty in projects-a new perspective, Int. J. Proy. Management, 26, 73-79.

Pujol, G., Iooss, B., Janon A., *(2014).* Sensitivity: Sensitivity Analysis. R package version 1.10.1. http://CRAN.R-project.org/package=sensitivity

R Core Team *(2013).* R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL http://www.R-project.org/

Shi Q., & T. Blomquist, *(2012).* A new approach for project scheduling using fuzzy dependency structure matrix, International Journal of Project Management, 30, 503-510.

Srour I.M., Abdul-Malak M.U., Yessine A.A., & Ramadan M., *(2013).* A methodology for scheduling overlapped design activities based on dependency information, Automation in Construction, 29, 1-11.

Saltelli A., Ratto M., Andres T., Campolongo F., Cariboni J., Gatelli D., Saisana M., & Tarantola S., *(2008).* Global sensitivity Analysis: The primer, John Wiley & Sons Ltd.

Tienda P., & M. Romano, *(2011).* A matrix algorithm RUPSP/GRUPSP "no splitting allowed" for production planning under Lean Construction methodology based on production processes, Revista de la Construcción, 10 *(2)*, 90-103.