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MODEL FOR COST PREDICTION OF PREFABRICATED HOUSING

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Preliminary notes

The paper analyzes the application of neural networks on cost prediction of prefabricated housing, on more than 30 buildings. 17 variables have been identified in the prediction model, with the following performances: 83,8 % of predicted values had the deviation lower than 5 % and 12,9 % had the deviation lower than 10 %, in relation to actual values. The model was verified on 28 and validated on 3 buidings, with the deviation of 4,6 % against actual values. With this model contruction companies can, during tendering phase, effectively predict total cost of prefabricated housing and thus acquire competitive advantage in the market. Conclusion brings guidelines for the model's use in practice and gives recommendation for its further development.

Keywords: *building cost, prefabricated housing, prediction, model, neural networks*

Model za predviđanje cijene montažne gradnje

Prethodno priopćenje

U radu je analizirana primjena neuralnih mreža prilikom procjene cijene montažne gradnje na više od 30 objekata. Identificirano je 17 varijabli pomoću kojih se može predvidjeti konačna cijena: 83,8 % predviđenih vrijednosti nalazilo se u granicama odstupanja do 5 %, a 12,9 % u granicama od 5-10 % od stvarnih vrijednosti. Model je verificiran na 28 i validiran na 3 nova objekta, s prosječnim odstupanjem od 4,6 % od stvarnih vrijednosti. Članak predstavlja model pomoću kojeg građevinska poduzeća, još u fazi nuđenja, mogu efektivno predviđati konačnu cijenu motažne gradnje. U zaključku su dane smjernice primjene modela u praksi i područja daljnjeg istraživanja.

Ključne riječi: *cijena, montažna gradnja, predviđanje, model, neuralne mreže*

1
Uvod
Introduction

Construction industry is mainly project oriented, even though some managers and engineers are still not aware of this fact. Acceleration of competitive, political and economic pressures in the industry has become an aggravating circumstance for achieving basic project management criteria, i.e. cost, time and scope. Thus, companies have to be more and more accurate in predicting total cost of building, still during the tendering phase. Nowadays only 34 % of projects make it in time, within the budget and in accordance with the agreed scope [1]. Because of this bad performance the construction has been proclaimed the worst, inefficient, plundering etc. [2].

Neural networks (NN) are a form of artificial intellegence (AI). The try to simulate behaviour of human's brain. The first model was published in 1943 by McCulloch and Pitts [3] where the authors analysed fundamental logic functions. Besides McCulloch and Pitts; Hebb [4], Lashley [5], Minsky [6], Rosenblatt i Wightman [7] served as a catalyst of change and promotors of NNs. After initial fame, up to 1980s and the IT dawn, NNs were developing in a lower pace, considering only smaller improvement [8-12]. Rapid development of IT stimulated the application of NN.

Furthermore, NN can be also found in researches in construction management; Chua et al. [13] studied the influence of critical success factors on planned construction cost. Ling et al. [14] defined a set of indicators that can predict project performance in Design & Build projects. They found strong correlation between 65 success factors and 11 criteria of project succes. Odeh et al [15] studied a set of indicators in correlation with project time, in traditional, construction management procurement routes. Kog et al. [16] designed a model using NN in predicting the deviation of project time. Iyer et al. [17] analysed more than 1500 projects in India and found reliable set of factors for prediction of cost in traditional building projects. Today, NN can be found in many areas besides construction, e.g.: finance, ICT, medicine, transport etc.

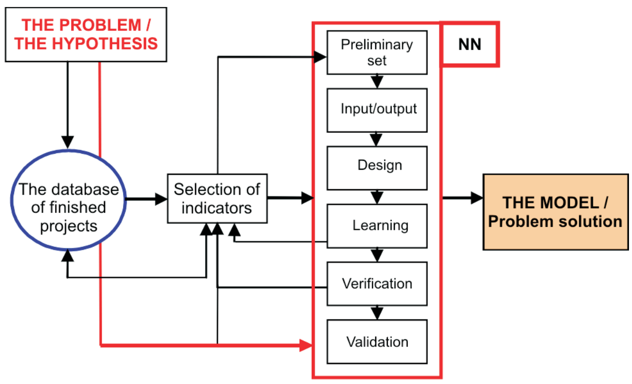

Figure 1 *Overview of the methodology*
Slika 1. *Pregled metodologije*

This paper elaborates the potential of NN on prefabricated housing. It examines and identifies variables that are corralated with the final cost of building. It proposes a NN based model for cost prediction, based on the final set of 17 validated factors, with which companies can in real time come up with accurate total cost of building.

2
The problem and the hypotheses
Problem i hipoteze istraživanja

The prediction problem in prefabricated housing is becoming more and more apparent, especialy in Croatia, where the market has become open with more than 9 000 construction companies present. Every day construction companies have to produce numerous bids, where investors do not have any obligation to even consider them. The gap among realized and unrealized bids is becoming more and more evident. This can only indicate low performance of construction companies in calculating the final cost of building. This problem is becoming even more significant if we put this problem in relation with customer loyality and long term relations.

All these issues and the fact that one of the authors is working in the prefabricated industry, enhanced the need of developing a model for efficient and effective cost prediction and thus solve the above mentioned problem. Therefore the hypothesis of this research was defined as:

H: The final cost of prefabricated housing can be predicted, in reasonable deviation boundaries, using Neural Networks on a critical set of factors.

3
The methodology
Metodologija istraživanja

The methodology of this reseach is presented in Figure 1. The research problem and the hypothesis (STEP 1, elaborated in the previous section) was the initial step of the model. After the first step, we approached the problem in defining the database (DB) (STEP 2). At first the DB included all information of finished projects (35 indicators), but as we were developing the model, the number of variables decreased (STEP 3). The initial selection of the indicators (STEP 4) was based on heuristics and experience of the authors. Mean cost/m^2 ratio served as a filter in identifing outliers in the set. From initial set of 35 indicators, three outliers were discarderded. The inputs (project indicators) and the output (total building cost) were defined in STEP 5. STEP 6 (design of the network) and STEP 7 were iterative processes, where number of iterations depended on NN's performance (STEP 8).

During the verification phase (STEP 8), actual cost vs. predicted cost performance was compared in order to verify the inputs. The final verification performance was evaluated using statistical indicators, i.e. R square and standard deviation. If a significant deviation in predicted values was found – the initial set was altered (and the variables were changed). Moreover if a variable had no influence on the output, it was discarded from the set. Thus, after altogether 12 verification iterations, the initial set of 32 variables was reduced on to 17 factors which were successfuly verified on 28 projects.

Finally, validation (STEP 9) was conducted on a new set of data (three new projects) that the model had not seen before. Afterwards, the validation performance was used to test the hypothesis.

4
The model features
Značajke modela

4.1
Selection of the best method of prediction for the model
Izbor najprikladnije metode za model

In our efforts to find the best solution for solving the research problem, besides NN, we had considered various methods, e.g. Linear regression, Nonlinear regression and Stepwise regression. In all our attempts we could not find as efficient models as NN for solving this kind of problem.

This was especially evident when we had to introduce new variables or discard the old ones from the set. Where regression models had some difficulties in adjusting to new variables, we found NNs as a very robust tool for such alterations in the model. This was actualy the main reason why NNs were selected for this model.

4.2
Limitations regarding different types of houses
Ograničenja u vezi različitih tipova kuća

Prefabricated housing, in this research, was considerd as facilities with prefabricated wooden bearing structure, of panel type. The total cost of building was considered as for the turn key projects, i.e. the cost of final completion and total functionality. The cost also cosidered all of the craft work included, i.e.: plumbing, HVAC etc.

The final cost did not comprehend: the cost of design, consulting fee, cost of land and infrastructure etc. The profit margin of 10 % was also included in the final cost. This kind of cost structure was introduced in the model because of the similar conditions on the Croatian market.

Furthermore, the model was designed only for family houses and not touristic or industrial facilities. Also, family houses were limited on to one and two floor buildings with the hight of one floor at 2,65 m.

4.3
Method limitations
Ograničenja metode

The hypothesis was tested in accordance with preset deviation boundaries. The boundaries were calibrated on:
< 10 % (±) acceptable for the contractor in the phase of negotiations
< 5 % acceptable for the contractor in the final offer .

5
Application of NN on the problem
Primjena NN-a na problem istraživanja

5.1
The identification of variables
Prepoznavanje varijabla

Variables were selected considering two crucial criteria of selection:

- influence of a variable on final outcome
- interrelation of one variable on the other.

Also, variables had to be specific and easilly calculated so contractors could come up with accurate prediction during negotiations with potential investor. Otherwise, the whole concept of swift prediction becomes a redundancy in the procurement process. Table 1 shows the final, verified and validated, set of 17 variables.

Table 1 also shows two types of variables; ones with preset quality levels and ones with numerical values that have to be calculated in respect to specific house dimensions.

There were two types of quality levels. Ones with predefined intervals from 1 to 3 (e.g. V.ZID) and ones with predefined intervals form 1 to 2 (e.g. EL). The intervals were defined with respect to the different quality solutions,

***Table 1** The final set of variables for the cost prediction*
***Tablica 1.** Konačni skup varijabla za predviđanje cijene građenja*

Variable	Definition	Values
V.ZID	Outer wall – quality of outer wall is defined by different quality levels, in regard to different building materials, termodynamic properties etc. In accordance with Croatian market we defined three levels of quality.	1 - 3
ET. PLOCA	Ceilling. Two levels of quality: with visible beams and without visible beams.	1 - 2
POD. KON.	Floor. Two levels of quality dependent on floor covering.	1 - 2
STUB.	Staircase. Two types of staircases, dependent on building material.	1 - 2
STOL.	Carpentry. Three levels of quality, dependent on different material, i.e. wood, aluminum/wood or PVC.	1 - 3
EL.	Electrical instalation - Two levels of quality in regard to price levels.	1 - 2
C.GR.	Central heating - Two levels of quality in regard to price levels.	1 - 2
ViK	Plumbing and sanitation - Two levels of quality in regard to price levels.	1 - 2
A_{netto}	Net area. The area was calculated without any correction factors in regard to attic .	numeric
$A_{\mathrm{Netto/Brutto}}$	Ratio between the net and gross area. The gross area was calculated as area in between outer walls.	numeric
$A_{\mathrm{proz}}/L_{\mathrm{v.zida}}$	Ratio between area of windows and total length of outer walls	numeric
$A_{\mathrm{gal}}/A_{\mathrm{br.ptk}}$	Ratio of area of gallery against gross area of the attic. The gallery is defined as a part of the ceilling where no cielling was built. Gallery area did not involve the area of the stairs.	numeric
$A_{\mathrm{pokr}}/A_{\mathrm{tl.krov}}$	Ratio of roof area against ortogonal area of the roof.	numeric
$H_{\mathrm{nad}}/2{,}65$ m	Ratio between the hight of ceilling wall and the height of one floor (2.65 m).	numeric
$L_{\mathrm{str}}/L_{\mathrm{zab.}}$	The ration between total leght of the roof on longitudinal side against total length of the roof on the gable.	numeric
$A_{\mathrm{kehlb}}/A_{\mathrm{ploce}}$	The ratio of ground floor ceilling area agains 1st floor ceiling area.	numeric
$A_{\mathrm{ter}}/A_{\mathrm{br.pr.}}$	The ratio of gross area of covered terace against ratio of the total gross area.	numeric

e.g.: materials, equipment, energy savings etc. All these variables were in correlation with market conditions, e.g. type of staircase (STUB.) and not with dimensions of houses. These atributes had to be included in the model, since total bulding cost of a prefabricated house can vary in regard to: different building materials, equipement price levels etc. The market variables were defined in respect of the authors experience on Croatian housing market. At first we started with 15 variables and, after verification phase (STEP 8), came with final 8 variables with predefined values (see Table 1).

Numeric variables were dependent on physical dimension of the houses (e.g. house net area, ratio of roof area against ortogonal area of the roof, etc). At first we started verification with 20 variables that the authors found significant for the prediction process. After verification (STEP 8), we discarded 11 variables that had no influence on the total cost. At the end of learning process we came with final 9 numeric variables (see Table 1). The following paragraph will explain only three variables (because of brevity of the paper). For explanation of the other variables, readers are encouraged to contact one of the authors.

$\boldsymbol{A_{\mathrm{netto}}}$ represents the net area of observed house. We have choosen this factor bacause of its strong correlation with the final cost, proven in practice [10, 17]. In the initial set we were also considering gross area, but during NN training we observed smaller influence on final outcome (Total cost) than we did with the net area. Another reason was that every house had a gallery and the gross area would not serve as such a good indicator.

$\boldsymbol{A_{\mathrm{Netto/Brutto}}}$ – This variable directly explains interior architecture, outer walls, thermal protection etc. E.g., if this variable is low then there will be many inner walls and stronger (thicker) outer walls.

$\boldsymbol{H_{\mathrm{nad}}/2{,}65}$ –This variable shows weather there is an attic or not. Also, this variable shows the minimum hight of the attic floor. $\boldsymbol{H_{\mathrm{nad}}}$ represents the hight of attic outer walls.

5.2 The input data
Ulazni podaci

After the initial outlier filtering, the set of 32 indicators was subjected to NN training in Neuro Shell 2 application (Release 4.0., Ward System Group, Inc). Table 2 shows input and output data for Nero Shell 2.

Values that were calculated as 0 were replaced with 0,001 (see Table 2, e.g. OBJ 16), since otherwise NN would not recognized the input and would consider it as missing data.

5.3 The network design and the learning procedure
Dizajn i process učenja neuralne mreže

The data was trained on different NN architectures, different training and different termination criteria. Also design phase considered different numbers of neurons in order to find an optimal solution. If we noticed a week influence of an indicator on the output we removed it form the set. In total, we had run over 20 different architectures until we came with the optimal design and the final set consisting of 17 indicators (see Table 1).

Table 2 *Overview of the input and the output data in the NN model*
Tablica 2*. Pregled ulaznih i izlanih podataka u modelu*

	V. ZID	ET. PLOČA	POD. KON.	STUB.	STOL.	EL.	C. GR.	ViK	A_{netto}	$A_{Netto/Brutto}$	$A_{proz}/L_{v.zida}$	$A_{gal}/A_{br.ptk}$	$A_{pokr}/A_{tl.krov}$	H_{nad}/2,65 m	$L_{str}/L_{zab.}$	A_{kehlb}/A_{ploce}	$A_{ter}/A_{br.pr.}$	Total cost, kn
OBJ 1	3	1	2	2	2	2	2	2	135,87	0,8472	0,49	0,0078	1,27	0,2754	0,51	0,58	0,001	701.499,52
OBJ 2	1	2	1	1	1	1	1	1	149,82	0,8498	0,47	0,0482	1,33	0,1321	0,56	0,49	0,04	558.809,54
OBJ 3	2	1	1	1	1	1	1	1	162,91	0,8257	0,31	0,0295	1,28	0,3773	0,89	0,52	0,03	607.838,58
OBJ 4	3	2	2	2	3	2	2	2	154,92	0,8538	0,23	0,001	1,32	0,1283	0,56	0,52	0,001	741.073,33
OBJ 5	2	1	1	1	2	1	2	1	198,39	0,8629	0,25	0,0485	1,08	0,4905	0,85	0,36	0,04	689.093,88
OBJ 6	1	2	1	1	1	1	1	1	108,40	0,8226	0,32	0,001	1,39	0,3698	0,76	0,55	0,001	463.718,39
OBJ 7	3	2	2	2	2	2	2	2	189,86	0,8560	0,35	0,001	1,37	0,2868	0,99	0,52	0,001	828.784,36
OBJ 8	2	1	1	1	1	1	1	1	140,78	0,8447	0,28	0,0533	1,27	0,0981	0,83	0,37	0,08	512.498,40
OBJ 9	1	1	1	1	1	1	1	1	154,68	0,8528	0,4	0,001	1,22	0,5698	0,87	0,52	0,001	556.143,24
OBJ 10	2	2	2	2	2	1	1	2	181,31	0,8539	0,53	0,0447	1,32	0,3018	0,64	0,56	0,03	766.131,00
OBJ 11	3	1	2	2	3	2	2	2	132,66	0,8427	0,29	0,001	1,41	0,1698	0,75	0,49	0,13	686.075,83
OBJ 12	2	2	1	1	1	1	1	1	141,86	0,8231	0,31	0,0571	1,26	0,1132	0,84	0,35	0,06	528.189,72
OBJ 13	1	1	1	1	1	1	2	1	245,93	0,8784	0,48	0,0473	1,13	0,7547	0,86	0,76	0,03	815.195,41
OBJ 14	3	1	2	2	2	2	2	2	209,79	0,8540	0,38	0,001	1,22	0,4528	1,29	0,64	0,05	933.829,26
OBJ 15	2	1	1	1	1	1	1	1	131,35	0,8371	0,25	0,001	1,31	0,1283	0,52	0,52	0,02	513.529,67
OBJ 16	1	0,001	1	0,001	1	1	1	1	103,87	0,8673	0,29	0,001	1,15	0,001	0,001	0,001	0,12	405.594,65
OBJ 17	2	0,001	1	0,001	2	1	1	1	123,85	0,8729	0,69	0,001	1,15	0,001	0,001	0,001	0,08	478.294,60
OBJ 18	1	0,001	1	0,001	1	1	1	1	56,55	0,8260	0,29	0,001	1,1	0,001	0,001	0,001	0,001	271.332,90
OBJ 19	2	0,001	2	0,001	2	1	2	1	93,82	0,8563	0,32	0,001	1,18	0,001	0,001	0,001	0,07	456.011,88
OBJ 20	3	0,001	2	0,001	3	2	2	2	140,03	0,8652	0,36	0,001	1,15	0,001	0,001	0,001	0,17	687.015,32
OBJ 21	1	0,001	1	0,001	1	1	1	1	93,13	0,8614	0,25	0,001	1,23	0,001	0,001	0,001	0,04	361.531,24
OBJ 22	3	0,001	2	0,001	3	2	2	2	139,13	0,8654	0,44	0,001	1,15	0,001	0,001	0,001	0,06	666.780,95
OBJ 23	2	0,001	2	0,001	2	2	1	2	123,74	0,8673	0,14	0,001	1,16	0,001	0,001	0,001	0,13	549.856,37
OBJ 24	1	0,001	1	0,001	1	1	1	1	134,99	0,8806	0,66	0,001	1,18	0,001	0,001	0,001	0,03	491.374,22
OBJ 25	3	0,001	2	0,001	2	2	2	2	104,64	0,8601	0,34	0,001	1,15	0,001	0,001	0,001	0,001	544.925,37
OBJ 26	2	0,001	2	0,001	3	2	2	2	135,52	0,8614	0,48	0,001	1,18	0,001	0,001	0,001	0,06	671.687,29
OBJ 27	3	0,001	2	0,001	2	2	2	2	121,68	0,8654	0,58	0,001	1,15	0,001	0,001	0,001	0,04	619.887,22
OBJ 28	1	0,001	1	0,001	1	1	1	1	115,45	0,8620	0,37	0,001	1,08	0,001	0,001	0,001	0,07	443.711,94

During the training procedure, we found that the most convenient network was 3 *Layer Backprop with Jump Connections*, from the group of *recommended classification net* and the *Output Layer Dampened Feedback Link,* from the group of *recommended predictive nets*.

5.4 Verification of the model
Verifkacija modela

Besides the architecture, network's efficiency was dependent on training time period. Thus, too trained network would give the best results on training input (the data during verification phase), but would not perform as well on the new data (three new houses introduced to the network during validation phase). In other words, good verification performance did not indicate good validation performance. Table 3 shows unfavourable and favourable verification performances that we came upon while training the network.

Table 3 *The comparison of favorable and unfavourable values in the verification phase*
Tablica 3. *Usporedba zadovoljavajućih i nezadovoljavajućih vrijednosti verifikacije modela*

Statistics	Favourable values	Unfavourable values
R^2	0,9373	0,9809
r^2	0,9375	0,9824
Square mean error	1391,588	422,622
Absolute mean error	28,381	12,827
Min. mean error	0,348	0,432
Max mean error	80,446	61,837
Correlation (r)	0,9682	0,9912
percentage under 5 %	60,714	85,714
percentage between 5 % and 10 %	25,000	10,714
percentage between 10 % and 20 %	10,714	3,571
percentage between 29 % and 30 %	3,571	0
percentage over 30 %	0	0

5.5 Validation of the model
Validacija modela

Validation was conducted on three, new objects, each one with different characteristics.

Table 4 *Comparison of actual vs. predicted values during the validation*
Tablica 4. *Usporedba stvarnih i predviđenih vrijednosti tijekom validacije modela*

Actual cost	Predicted cost (NN)	Deviation	%
556,7750244	560,5253296	-3,750305176	-0,67
450,618988	429,5108948	21,10809326	4,68
731,3359985	778,3654175	-47,02941895	-6,43

Table 4 shows deviation of predicted total cost against actual cost. The validation showed that the predictions gained through the NN model were within preset boundaries and were very acceptable for the model. Mean deviation was only at 4,13 %. Another interesting fact was the comparison of the verification and the validation data (see Table 5).

Table 5 *Comparison of the verification and the validation performances*
Tablica 5. *Usporedba rezultata verifikacije i validacije modela*

Output	Verification	Validation
R^2	0,9809	0,9781
r^2	0,9824	0,9783
Square mean error	422,622	467,896
Absolute mean error	12,827	13,905
Min. mean error	0,432	0,432
Max mean error	61,837	61,837
Correlation (r)	0,9912	0,.9891
percentage under 5 %	85,714	83,871
percentage between 5 % and 10 %	10,714	12,903
percentage between 10 % and 20 %	3,571	3,226
percentage between 29 % and 30 %	0	0
percentage over 30 %	0	0

Taking into consideration values from Table 5 it can be noticed that performance of the model has just slightly decreased after validation. So, it was concluded that the network was enough stable and trained on to a satisfactory level.

6
The discussion: analysis of results and the use of the model
Diskusija: analiza rezultata i upotrebe modela

This paper has proven that by using a critical set of variables construction companies can, in a very short time, with satisfactory accuracy, predict the total cost of prefabricated buildings.

The final set of factors consists of 17 variables, which are: V.ZID, ET. PLOCA, POD. KON., STUB., STOL., EL., C.GR., ViK, A_{netto}, $A_{Netto/Brutto}$, $A_{proz}/L_{v.zida}$, $A_{gal}/A_{br.ptk}$, $A_{pokr}/A_{tl.krov}$, $H_{nad}/2{,}65$ m, $L_{str}/L_{zab.}$, A_{kehlb}/A_{ploce}, $A_{ter}/A_{br.pr.}$.

Validation performance was on satisfactory level. Minimum deviation of predicted from actual value was on 0,67 %, mean on 4,13 % and maximum deviation on 6,43 %. All these facts indicated that we had the model trained enough.

Therefore, the hypothesis:
The final cost of prefabricated housing can be predicted, in reasonable deviation boundaries, using Neural Networks on a critical set of factors

was tested and accepted.

It also has to be noted that the model will become more and more robust as the database will grows and so NN's efficiency will improve [13]. From this reason, construction companies should accept the final set of variables and fill it with new data whenever a new project is delivered.

Practical value of this research is to be found in the possibility that companies can in real time effectively respond to client request, while consuming as little time and resources as possible.

7
Conclusion
Zaključak

The research has justified the hypothesis and has proven that companies can very accurately predict total cost of prefabricated housing in a very efficient way. Also, this kind of model will help professionals in dealing with market pressures. Using this model, bidders and all others who are dealing with cost prediction can more effectively respond to market needs.

In further research some limitations have to be removed: e.g. the model has to be developed for facilities other than residential, consider not just 1st floor houses, introduce administrative costs and add some financial variables (i.e. net present value, return of investment etc.). Authors are also of opinion that the model has to be expanded on to traditional building (brick, concrete etc.) as well, especialy due to its popularity in Croatia.

In the following years, the construction ought to start using this kind of methods and thus proactively start coping with changes and start improving the sector.

8
Literature
Literatura

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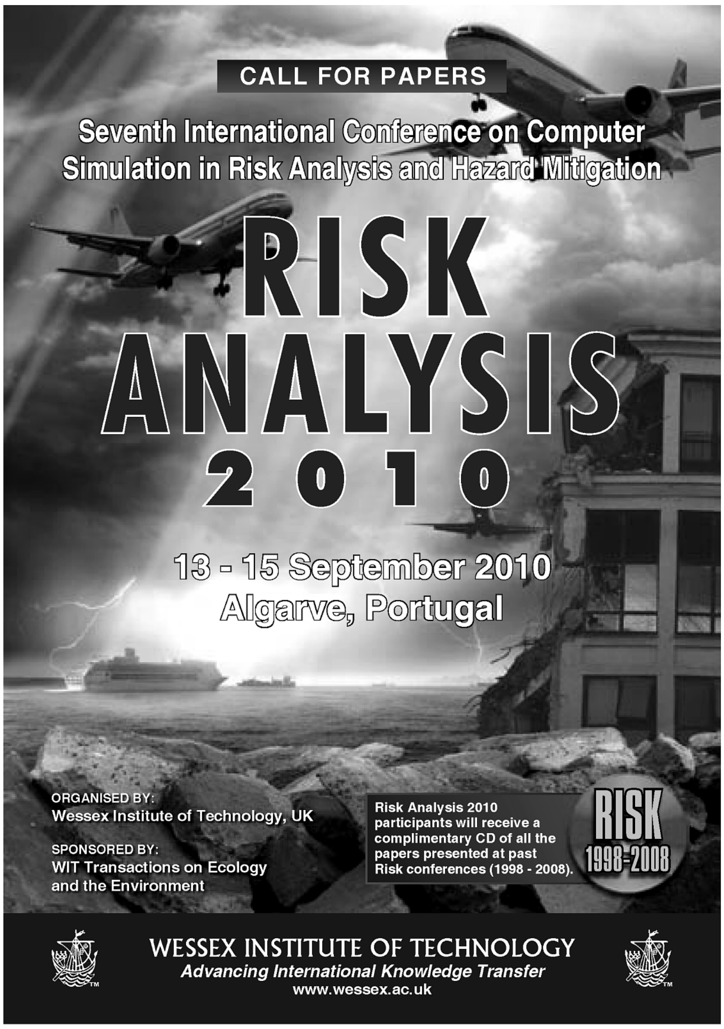
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