

An Intelligent Approach to Software Cost Prediction

Xishi Huang, Danny Ho¹, Luiz F. Capretz, Jing Ren

Dept. of ECE, University of Western Ontario, London, Ontario, N6G 1H1, Canada
¹Toronto Design Center, Motorola Canada Ltd., Markham, Ontario, L6G 1B3, Canada

{xhuang22, lcapretz, jren2}@uwo.ca, Danny.Ho@motorola.com

October 22, 2003



Agenda

- **Problem**
- The Novel Neuro-Fuzzy Model
- Validation by Industry Project Data
- Conclusion and Future Work



Software Cost Estimation

Motivation:

- Many software projects go over time and budget
- Software development has become an essential investment for many organizations

Problem Statement:

- We use project information such as software size and other attributes to predict software cost or effort

Characteristics of Software Cost Estimation:

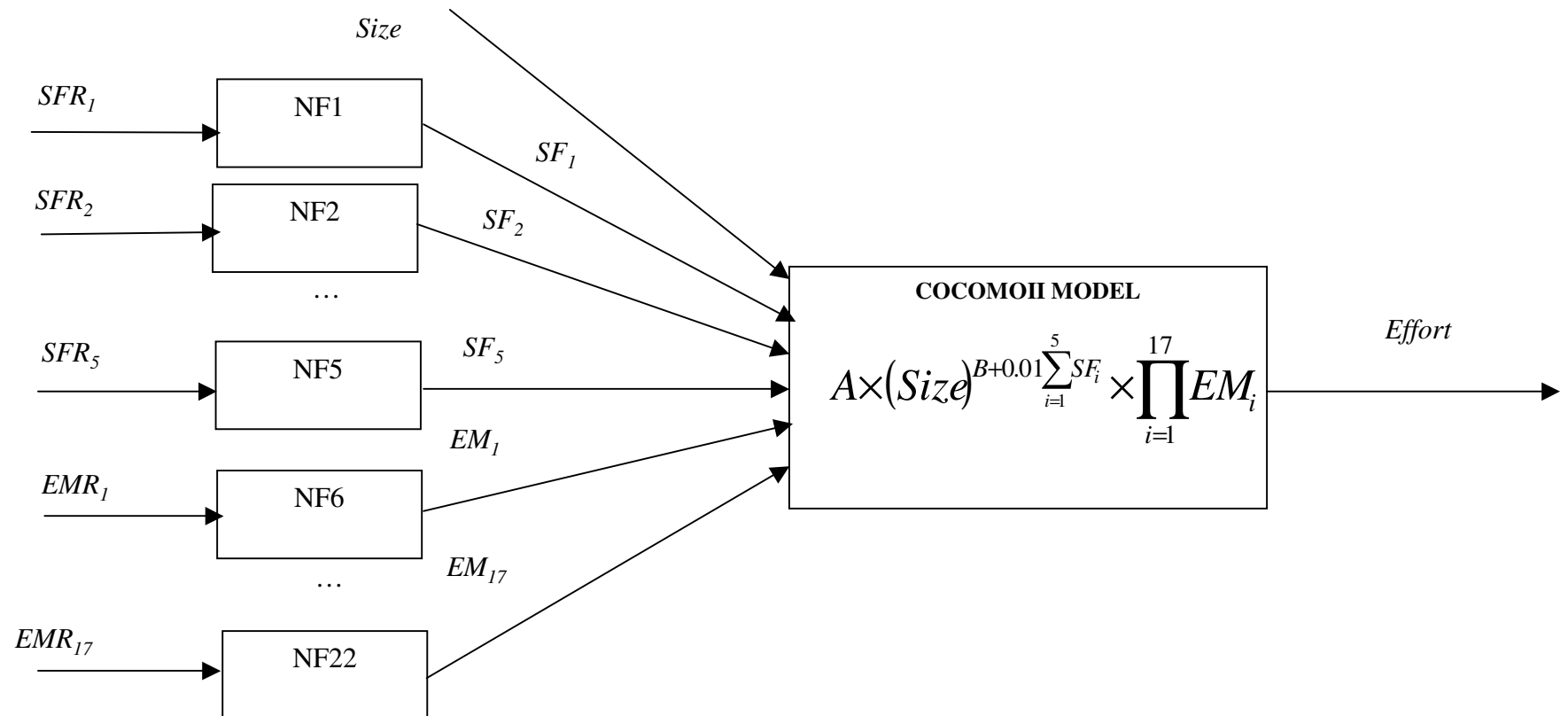
- Complex nonlinear relationships between software development cost and cost drivers
- Imprecise and uncertain measurement
- Rapid change of software technology and processes



Agenda

- Problem
- **A Novel Neuro-Fuzzy Model**
- Validation by Industry Project Data
- Conclusion and Future Work

A Novel Neuro-Fuzzy COCOMO Model





COCOMO Model

- COCOMO II Post Architecture Model

$$Effort = A \times (Size)^{B+0.01 \times \sum_{i=1}^5 SF_i} \times \prod_{i=1}^{17} EM_i$$

where:

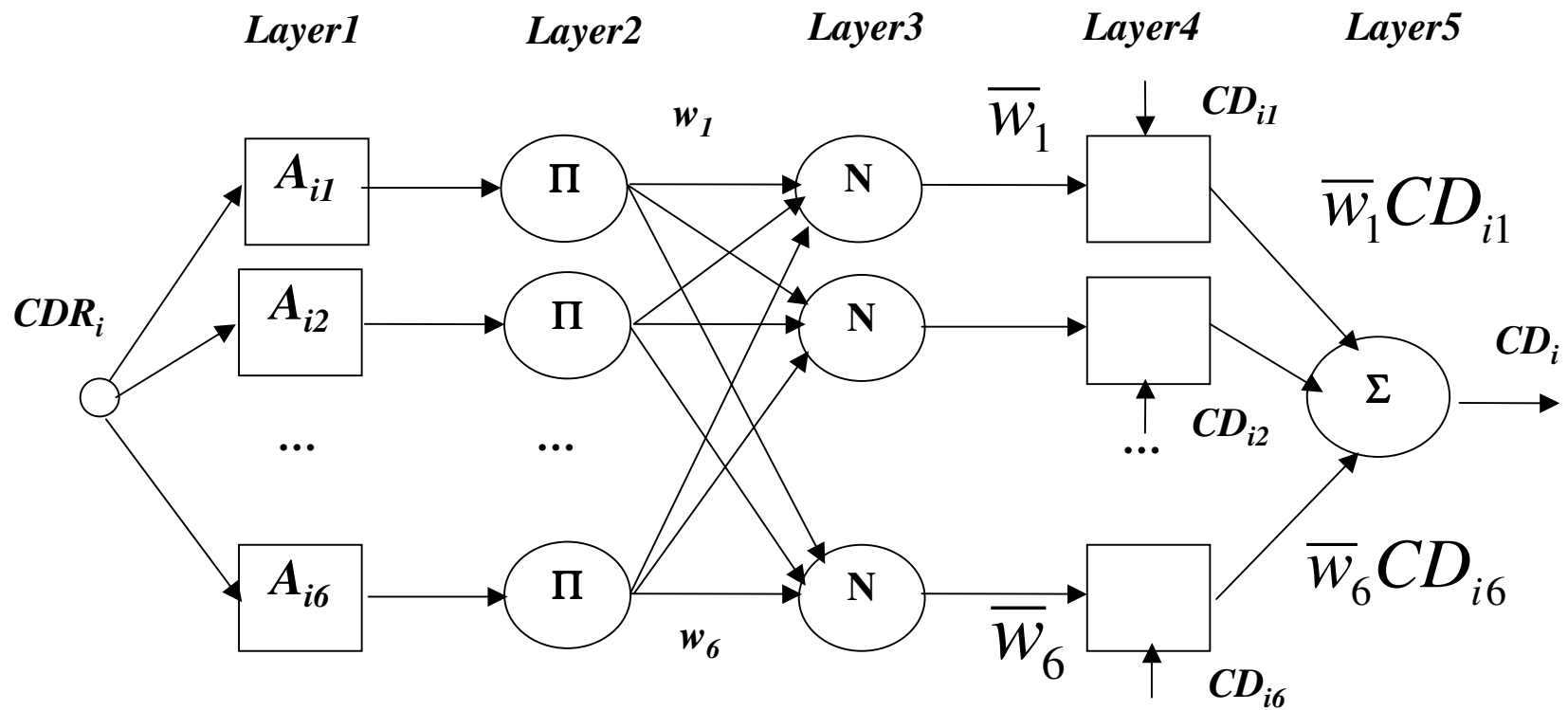
- effort is in staff-month (SM)
- A,B are constants
- Size is in KSLOC
- SF_i 's are scale factors
- EM_i 's are effort multipliers



Some Notations

Fuzzy Sets		Rating Levels	Parameter Values
A_{i1}	1	Very Low (VL)	CD_{i1}
A_{i2}	2	Low (L)	CD_{i2}
A_{i3}	3	Nominal (N)	CD_{i3}
A_{i4}	4	High (H)	CD_{i4}
A_{i5}	5	Very High (VH)	CD_{i5}
A_{i6}	6	Extra High (XH)	CD_{i6}

Sub-Model NF_i



CDR_i : continuous rating value

CD_i : corresponding numerical value



Reasoning Phase: Fuzzy rules

- If CDR_i is A_{i1} (VL), then $CD_i = CD_{i1}$,
 - If CDR_i is A_{i2} (L), then $CD_i = CD_{i2}$,
 - If CDR_i is A_{i3} (N), then $CD_i = CD_{i3}$,
 - If CDR_i is A_{i4} (H), then $CD_i = CD_{i4}$,
 - If CDR_i is A_{i5} (VH), then $CD_i = CD_{i5}$,
 - If CDR_i is A_{i6} (XH), then $CD_i = CD_{i6}$.
- $(i,k), i=1,2,\dots,22, k=1,2,\dots,6$



Sub-Model NF_i (Cont'd)

- Layer 1: $O_k^1 = \mu_{ik}(x)$
- Layer 2: $w_k = \prod \mu_{ikj}(x)$
- Layer 3: $\bar{w}_k = \frac{\dot{w}_k}{\sum w_j}$
- Layer 4: $O_k^4 = \bar{w}_k CD_{ik}$
- Layer 5: $CD_i = \sum_k \bar{w}_k CD_{ik}$



Interpretation of sub-model NF_i

Linear interpolation:

$$\mu_{ik}(x) = \begin{cases} x - (k - 1), & k - 1 \leq x \leq k \\ (k + 1) - x, & k \leq x \leq k + 1 \\ 0, & \textit{otherwise} \end{cases}$$

$$CD_i = CD_{ik} + (CD_{ik+1} - CD_{ik})(CDR_i - k)$$

$$k \leq CDR_i \leq k + 1, k = 1, 2, \dots, 6$$



Learning Algorithms

Optimization problem:

$$E = \sum_{n=1}^{NN} \frac{1}{2} w_n \left(\frac{E_n - E_{dn}}{E_{dn}} \right)^2$$

subject to monotonic constraints:

$$CD_{i1} \leq CD_{i2} \leq CD_{i3} \leq CD_{i4} \leq CD_{i5} \leq CD_{i6}, i \in I_{INC}(CD)$$

$$CD_{i1} \geq CD_{i2} \geq CD_{i3} \geq CD_{i4} \geq CD_{i5} \geq CD_{i6}, i \in I_{DEC}(CD)$$

Learning Algorithm:

$$CD_{ik}^{l+1} = CD_{ik}^l - \alpha \frac{\partial E}{\partial CD_{ik}}$$



Advantage of Continuous Rating Values

Two similar projects P1 and P2 have the same nominal effort, say 100 staff-months.

The COCOMO II.2000 model,

- For P1, 203 staff-months
- For P2, 2886 staff-months!

The difference is over 14 times.

Our Model: 809 staff-months for both projects



Agenda

- Problem
- A Novel Neuro-Fuzzy Model
- **Validation by Industry Project Data**
- Conclusion and Future Work



Validation by Industry Project Data

Sources of Project Data

- Industrial project data: 6 projects
- COCOMO81 database: 63 projects



Validation Results

- Case I. Learning with all project data
- Case II. Learning with part of project data
- Case III. Use larger weights for local data
- Case IV. Learning without monotonic constraints



Effort estimation for all 69 project data points

ARE	COCOMO81 Model	Neuro-Fuzzy Model							
		Case I		Case II		Case III		Case IV	
	PERC	PERC	IMPRV	PERC	IMPRV	PERC	IMPRV	PERC	IMPRV
20%	71%	86%	15%	88%	17%	88%	17%	89%	18%
30%	81%	92%	11%	92%	11%	92%	11%	94%	13%



Effort estimation for industrial project data

Project No	Actual Effort	COCOMO81 Model		Neuro-Fuzzy Model					
				Case I		Case II		Case III	
		Estimate	Error	Estimate	Error	Estimate	Error	Estimate	Error
P1	638.0	827.0	29%	745.0	16%	739.7	15%	728.6	14%
P2	185.0	152.2	-17%	167.3	-9%	166.1	-10%	163.6	-11%
P3	332.0	279.8	-15%	322.0	-3%	306.8	-7%	325.5	-1%
P4	619.9	701.4	13%	651.5	5%	651.7	5%	642.0	3%
P5	64.8	71.1	9%	63.4	-2%	60.8	-6%	64.1	-1%
P6	76.6	83.1	8%	72.2	-5%	72.3	-5%	73.8	-3%



Agenda

- Problem
- A Novel Neuro-Fuzzy Model
- Validation by Industry Project Data
- **Conclusion and Future Work**



Conclusion

- **Propose a novel neuro-fuzzy COCOMO model**
 - Neuro-fuzzy COCOMO structure
 - Monotonic constraints
 - Learning algorithm
 - Fuzzy rules



Conclusion (Cont'd)

Distinguishing Features of the Proposed Model:

- Learning ability
- Robust to imprecise and uncertain inputs
- Good Interpretability
- Knowledge integration
- Reduced number of learning parameters
- Good generalization
- Local learning



Future Work

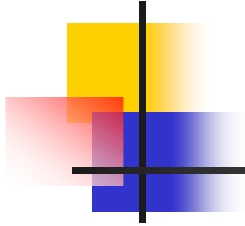
Extending the neuro-fuzzy approach to

- Other cost estimation models, e.g. SLIM
- Quality estimation models, e.g. COQUALMO

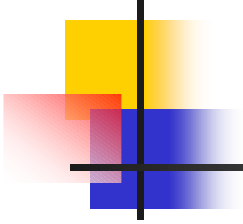


References

1. B. Boehm et al., *Software Cost Estimation with COCOMO II*, Prentice Hall PTR, Upper Saddle River, New Jersey 07458, 2000.
2. B. Boehm, *Software Engineering Economics*, Prentice-Hall, Inc., Englewood Cliffs, New Jersey 07632, 1981.
3. S. MacDonell and A. Gray, “A comparison of modeling techniques for software development effort prediction,” in *Proceedings of the 1997 International Conference on Neural Information Processing and Intelligent Information Systems*, Springer-Verlag, 1997, pp. 869–872.
4. S. Chulani, *Bayesian Analysis of Software Cost and Quality Models*, Ph.D. Dissertation, University of Southern California, 1999.
5. M. Shepperd and G. Kadoda, “Comparing software prediction techniques using simulation”, *IEEE Transactions on Software Engineering*, Vol. 27, No. 11, pp. 1014-1022, November 1999.
6. S. Mitra, “Neuro-fuzzy rule generation: survey in soft computing framework,” *IEEE Trans. on Neural Networks*, Vol. 11, pp. 748–768, May 2000.
7. R. Fuller. *Introduction to Neuro-Fuzzy Systems*, Physica-Verlag, Heidelberg, 2000.
8. R. J. S. Jang, “ANFIS: adaptive-network-based fuzzy inference system,” *IEEE Trans. Systems, Man, and Cybernetics*, Vol. 23, pp. 665-685, 1993.
9. D. Ho, “Experience report on COCOMO and the Costar tool from Nortel’s Toronto Laboratory,” in *Eleventh International Forum on COCOMO and Software Cost Modeling*, University of Southern California, Los Angeles, October 1996.
10. N. Panlilio-Yap and D. Ho, “Deploying software estimation technology and tools: the IBM SWS Toronto Lab experience,” in *Ninth International Forum on COCOMO and Software Cost Modeling*, University of Southern California, Los Angeles, October 1994.
11. T. Takaki and M. Sugeno, “Fuzzy identification of systems and its application to modeling and control”, *IEEE Trans. Syst., Man, Cybern.*, Vol. 15, pp.116-132, 1985.
12. X. Huang, *A Neuro-Fuzzy Model for Software Cost Estimation*, Master Thesis, Department of Electrical and Computer Engineering, The University of Western Ontario, July 2003.



THANKS !



Any Questions?