

Lecture Notes in Control and Information Sciences

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Neural Models of Language Processes,

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*Language Processing and Other Organisms, S.-J. Segalowitz et al.,
Hillsdale, NJ, 1983*

System Modeling and Optimization

Proceedings of the 10th IFIP Conference
New York City, USA, August 31 – September 4, 1981

Edited by R.F. Drenick and F. Kozin



Springer-Verlag
Berlin Heidelberg New York 1982

Applications of Advances in Nonlinear Sensitivity Analysis

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The following paper summarizes the major properties and applications of a collection of algorithms involving differentiation and optimization at minimum cost. The areas of application include the sensitivity analysis of models, new work in statistical or econometric estimation, optimization, artificial intelligence and neuron modelling. The details, references and derivations can be obtained by requesting "Sensitivity Analysis Methods for Nonlinear Systems" from Forecast Analysis and Evaluation Team, Quality Assurance, OSS/EIA, Room 7413, Department of Energy, Washington, DC 20461.

Context of the Work

The Energy Information Administration (EIA) provides data and analysis on all aspects of energy supply and demand. It uses dozens of models, including econometric (statistical, empirical) models, linear programming models based on technological data, a nonlinear micro equilibrium model solving for thousands of variables simultaneously across a 50-year span, hybrids and combinations of these, etc.

Many users of EIA's analyses do not accept EIA's conclusions at face value, especially when reports from other sources disagree. Thus the Forecast Evaluation and Analysis Team of EIA and its predecessors have carried out a broad program to evaluate and explain the qualitative assumptions of EIA models and forecasts. This program includes the development of tools to characterize the properties of large models, studies of estimation methods which are robust against outliers or model misspecification (i.e., correlated errors), proofs of convergence and existence properties, and many other projects. The first part of this paper describes how a small part of this work - the minimum cost calculation of first and second order derivatives of nonlinear systems - makes an essential contribution to the rest. The second part elaborates on another application, a method for stochastic optimization which becomes feasible only with the help of low-cost derivatives. This method opens up a wholly new approach to the field of artificial intelligence and neuron modelling; it is especially efficient with the new generation of "parallel" computers.

- $\underline{x}(t+1) = \underline{f}(\underline{x}(t), \underline{u}(t))$

- N components of \underline{x}
- m terms per equation f_i
- T time periods
- cost of simulation = mNT
- not a "simultaneous" (implicit) model

$$\frac{\partial^2 x_i(T)}{\partial x_j(1)}$$

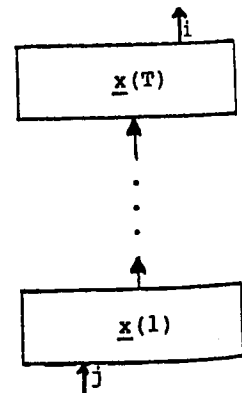


Figure 1: A Simple Example

Figure 1 shows a simple example of the kind of "derivative" we are trying to compute. Suppose that we have a nonlinear system, with a

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