

Which Method for Solution of the System of Interval Equations Should we Choose?

A. Pownuk¹, J. Quezada¹, I. Skalna²,
M.V. Rama Rao³, A. Belina⁴

- ¹ The University of Texas at El Paso, El Paso, Texas, USA
² AGH University of Science and Technology, Krakow, Poland
³ Vasavi College of Engineering, Hyderabad, India
⁴ Silesian University of Technology, Gliwice, Poland

21th Joint UTEP/NMSU Workshop on Mathematics,
Computer Science, and Computational Sciences

Outline

- 1 Solution Set
- 2 Optimization methods
- 3 Other Methods
- 4 Interval Methods
- 5 Comparison
- 6 Conclusions

Solution of PDE

Solution Set

Optimization
methods

Other
Methods

Interval
Methods

Comparison

Conclusions

Parameter dependent Boundary Value Problem

$$A(p)u = f(p), u \in V(p), p \in P$$

Exact solution

$$\underline{u} = \inf_{p \in P} u(p), \bar{u} = \sup_{p \in P} u(p)$$

$$u(x, p) \in [\underline{u}(x), \bar{u}(x)]$$

Approximate solution

$$\underline{u}_h = \inf_{p \in P} u_h(p), \bar{u}_h = \sup_{p \in P} u_h(p)$$

$$u_h(x, p) \in [\underline{u}_h(x), \bar{u}_h(x)]$$

Mathematical Models in Engineering

Solution Set

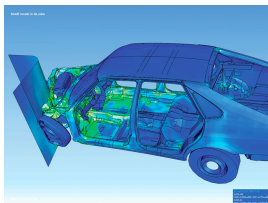
Optimization
methods

Other
Methods

Interval
Methods

Comparison

Conclusions



High dimension $n > 10000$.

Linear and nonlinear equations.

Multiphysics (solid mechanics, fluid mechanics etc.)

Ordinary and partial differential equations, variational equations, variational inequalities, numerical methods, programming, visualizations, parallel computing etc.

Two point boundary value problem

Solution Set

Optimization
methods

Other
Methods

Interval
Methods

Comparison

Conclusions

Sample problem

$$\begin{cases} -(a(x)u'(x)) = f(x) \\ u(0) = 0, u(1) = 0 \end{cases}$$

and $u_h(x)$ is finite element approximation given by a weak formulation

$$\int_0^1 a(x)u'_h(x)v'(x)dx = \int_0^1 f(x)v(x)dx, \forall v \in V_h^{(0)}$$

or

$$a(u_h, v) = l(v), \forall v \in V_h^{(0)} \subset H_0^1$$

where $u_h(x) = \sum_{i=1}^n u_i \varphi_i(x)$ and $\varphi_i(x_j) = \delta_{ij}$.

The Finite Element Method

Solution Set

Optimization
methods

Other
Methods

Interval
Methods

Comparison

Conclusions

Approximate solution $\int_0^1 a(x)u'_h(x)v'(x)dx = \int_0^1 f(x)v(x)dx.$

$$\sum_{j=1}^n \left(\sum_{i=1}^n \int_0^1 a(x)\varphi_i(x)\varphi_j(x)dx u_i - \int_0^1 f(x)\varphi_j(x)dx \right) v_j = 0$$

Final system of equations (for one element) $Ku = q$ where

$$K_{i,j} = \int_0^1 a(x)\varphi_i(x)\varphi_j(x)dx, q_i = \int_0^1 f(x)\varphi_i(x)dx$$

Calculations of the local stiffness matrices can be done in parallel.

Global Stiffness Matrix

Solution Set

Optimization
methods

Other
Methods

Interval
Methods

Comparison

Conclusions

Global stiffness matrix

$$\sum_{p=1}^n \left(\sum_{q=1}^n \sum_{e=1}^{n_e} \sum_{i=1}^{n_u^e} \sum_{j=1}^{n_u^e} U_{j,p}^e \int_{\Omega_e} a(x) \frac{\partial \varphi_i^e(x)}{\partial x} \frac{\partial \varphi_j^e(x)}{\partial x} dx U_{i,q}^e u_q - \right.$$

$$\left. \sum_{q=1}^n \sum_{e=1}^{n_e} \sum_{i=1}^{n_u^e} \sum_{j=1}^{n_u^e} U_{j,p}^e \int_{\Omega_e} f(x) \varphi_i^e(x) \varphi_j^e(x) dx \right) v_p = 0$$

Final system of equations

$$K(p)u = Q(p) \Rightarrow F(u, p) = 0$$

Computations of the global stiffness matrix can be done in parallel.

Solution Set

Solution Set

Optimization
methods

Other
Methods

Interval
Methods

Comparison

Conclusions

Nonlinear equation $F(u, p) = 0$ for $p \in P$.

$$F : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}^n$$

Implicit function $u = u(p) \Leftrightarrow F(u, p) = 0$

$$u(P) = \{u : F(u, p) = 0, p \in P\}$$

Interval solution

$$\underline{u}_i = \min\{u : F(u, p) = 0, p \in P\}$$

$$\bar{u}_i = \max\{u : F(u, p) = 0, p \in P\}$$

Interval Methods

Solution Set

Optimization
methods

Other
Methods

Interval
Methods

Comparison

Conclusions

A. Neumaier, Interval Methods for Systems of Equations (Encyclopedia of Mathematics and its Applications, Cambridge University Press, 1991).

Z. Kulpa, A. Pownuk, and I. Skalna, Analysis of linear mechanical structures with uncertainties by means of interval methods, Computer Assisted Mechanics and Engineering Sciences, 5, 443-477, 1998.

V. Kreinovich, A.V.Lakeyev, and S.I. Noskov. Optimal solution of interval linear systems is intractable (NP-hard). Interval Computations, 1993, 1, 6-14.

Optimization methods

Solution Set

Optimization
methods

Other
Methods

Interval
Methods

Comparison

Conclusions

Interval solution

$$\underline{u}_i = \min\{u(p) : p \in P\} = \min\{u : F(u, p) = 0, p \in P\}$$

$$\bar{u}_i = \max\{u(p) : p \in P\} = \max\{u : F(u, p) = 0, p \in P\}$$

$$\underline{u}_i = \begin{cases} \min u_i \\ F(u, p) = 0 \\ p \in P \end{cases}, \bar{u}_i = \begin{cases} \max u_i \\ F(u, p) = 0 \\ p \in P \end{cases}$$

KKT Conditions

Solution Set

Optimization
methods

Other
Methods

Interval
Methods

Comparison

Conclusions

Nonlinear optimization problem for $f(x) = x_i$

$$\begin{cases} \min_x f(x) \\ h(x) = 0 \\ g(x) \geq 0 \end{cases}$$

Lagrange function $L(x, \lambda, \mu) = f(x) + \lambda^T h(x) - \mu^T g(x)$

Optimality conditions can be solved by the Newton method.

$$\begin{cases} \nabla_x L = 0 \\ \nabla_\lambda L = 0 \\ \mu_i \geq 0 \\ \mu_i g_i(x) = 0 \\ h(x) = 0 \\ g(x) \geq 0 \end{cases}$$

KKT Conditions - Newton Step

Solution Set

Optimization
methods

Other
Methods

Interval
Methods

Comparison

Conclusions

$$F'(X)\Delta X = -F(X)$$

$$F'(X) = \begin{bmatrix} (\nabla_x^2 f(x) + \nabla_x^2 h(x)y)_{n \times n} & \nabla_x h(x)_{n \times m} & -I_{n \times n} \\ (\nabla_x h(x))^T_{m \times n} & 0_{n \times m} & 0_{m \times n} \\ Z_{n \times n} & 0_{n \times m} & X_{m \times n} \end{bmatrix}$$

$$\Delta X = \begin{bmatrix} \Delta x \\ \Delta y \\ \Delta z \end{bmatrix}, X = \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

$$F(X) = - \begin{bmatrix} \nabla_x f(x) + \nabla_x h^T(x)y - z \\ h(x) \\ XYe - \mu_k e \end{bmatrix}$$

Steepest Descent Method

Solution Set

Optimization
methods

Other
Methods

Interval
Methods

Comparison

Conclusions

In order to find maximum/minimum of the function u it is possible to apply the steepest descent algorithm.

- 1 Given x_0 , set $k = 0$.
- 2 $d^k = -\nabla f(x_k)$. If $d^k = 0$ then stop.
- 3 Solve $\min_{\alpha} f(x_k + \alpha d^k)$ for the step size α_k . If we know second derivative H then $\alpha_k = \frac{d_k^T d_k}{d_k^T H(x_k) d_k}$.
- 4 Set $x_{k+1} = x_k + \alpha_k d_k$, update $k = k + 1$. Go to step 1.

I. Skalna and A. Pownuk, Global optimization method for computing interval hull solution for parametric linear systems, International Journal of Reliability and Safety, 3, 1/2/3, 235-245, 2009.

The Gradient

Solution Set

Optimization
methods

Other
Methods

Interval
Methods

Comparison

Conclusions

After discretization

$$Ku = q$$

Calculation of the gradient

$$Kv = \frac{\partial}{\partial p_k} q - \frac{\partial}{\partial p_k} Ku$$

where $v = \frac{\partial}{\partial p_k} u$.

Gradient Method and Sensitivity Analysis

A. Pownuk, Numerical solutions of fuzzy partial differential equation and its application in computational mechanics, in: M. Nikraves, L. Zadeh and V. Korotkikh, (eds.), Fuzzy Partial Differential Equations and Relational Equations: Reservoir Characterization and Modeling, Physica-Verlag, 308-347, 2004.

Postprocessing of the interval solution.

$$\varepsilon = Cu$$

$$\sigma = D\varepsilon$$

Linearization

Solution Set

Optimization
methods

Other
Methods

Interval
Methods

Comparison

Conclusions

$$\Delta f(x) = f(x + \Delta x) - f(x) \approx f'(x)\Delta x$$

Derivative can be calculated numerically.

$$f'(x) \approx \frac{f(x + h) - f(x)}{h}$$

The method can be used together with incremental formulation of the Finite Element Method.

$$K(p)\Delta u = \Delta Q(p)$$

Monte Carlo Simulation/Search Method

Solution Set

Optimization
methods

Other
Methods

Interval
Methods

Comparison

Conclusions

Monte Carlo Method (inner approximation of the solution set)

$$u(P) \approx \text{Hull}(\{u : K(p)u = Q(p), p \in \{\text{random values from } P\}\})$$

Search Method. $P \approx \{\text{special points}\}$

$$u(P) \approx \text{Hull}(\{u : K(p)u = Q(p), p \in \{\text{special points}\}\})$$

Vertex Method

$$u(P) \approx \text{Hull}(\{u : K(p)u = Q(p), p \in \{\text{set of vertices}\}\})$$

Cauchy Based Monte Carlo Simulation

Solution Set

Optimization
methods

Other
Methods

Interval
Methods

Comparison

Conclusions

$$\rho_{\Delta}(x) = \frac{\Delta}{\pi} \cdot \frac{1}{1 + x^2/\Delta^2}.$$

when $\Delta x_i \sim \rho_{\Delta_i}(x)$ are indep., then

$$\Delta y = \sum_{i=1}^n c_i \cdot \Delta x_i \sim \rho_{\Delta}(x), \text{ with } \Delta = \sum_{i=1}^n |c_i| \cdot \Delta_i.$$

Thus, we simulate $\Delta x_i^{(k)} \sim \rho_{\Delta_i}(x)$; then,

$$\Delta y^{(k)} \stackrel{\text{def}}{=} \tilde{y} - f(\tilde{x}_1 - \Delta x_1^{(k)}, \dots) \sim \rho_{\Delta}(x).$$

Maximum Likelihood method can estimate Δ :

$$\prod_{k=1}^N \rho_{\Delta}(\Delta y^{(k)}) \rightarrow \max, \text{ so } \sum_{k=1}^N \frac{1}{1 + (\Delta y^{(k)})^2/\Delta^2} = \frac{N}{2}.$$

To find Δ from this equation, we can use, e.g., the bisection method for $\underline{\Delta} = 0$ and $\overline{\Delta} = \max_{1 \leq k \leq N} |\Delta y^{(k)}|$.

Theory of perturbations

Solution Set

Optimization
methods

Other
Methods

Interval
Methods

Comparison

Conclusions

J. Skrzypczyk¹, A. Belina, FEM ANALYSIS OF UNCERTAIN SYSTEMS WITH SMALL GP-FUZZY TRIANGULAR PERTURBATIONS, Proceedings of the 13th International Conference on New Trends in Statics and Dynamics of Buildings October 15-16, 2015 Bratislava, Slovakia Faculty of Civil Engineering STU Bratislava Slovak Society of Mechanics SAS

$$A = A_0 + \varepsilon^1 A_1 + \varepsilon^2 A_2 + \dots$$

J.D. Cole, Perturbation methods in applied mathematics, Bialsdell, 1968.

Interval Boundary Element Method

Solution Set

Optimization
methods

Other
Methods

Interval
Methods

Comparison

Conclusions

T. Burczynski, J. Skrzypczyk, Fuzzy aspects of the boundary element method, Engineering Analysis with Boundary Elements, Vol.19, No.3, pp. 209216, 1997

$$cu = \int_{\partial\Omega} \left(G \frac{\partial u}{\partial n} - \frac{\partial G}{\partial n} u \right) dS$$

Element by Element Method

Solution Set

Optimization
methods

Other
Methods

Interval
Methods

Comparison

Conclusions

Muhanna, R. L. and R. L. Mullen. Uncertainty in Mechanics Problems Interval-Based Approach, Journal of Engineering Mechanics 127(6), 557-566, 2001.

$$\Pi^* = \frac{1}{2} \{U\}^T [K] \{U\} - \{U\}^T \{P\} + \lambda_1^T ([C] \{U\} - \{V\}) + \lambda_2^T ([B_1] \{U\} - \{\kappa\}) \quad (40)$$

Invoking the stationarity of Π^* , that is $\delta \Pi^* = 0$, and considering Eq. (40), we obtain

$$\begin{pmatrix} \mathbf{0} & C^T & B_1^T & 0 \\ C & 0 & 0 & 0 \\ B_1 & 0 & 0 & -I \\ 0 & 0 & -I & 0 \end{pmatrix} + \begin{bmatrix} A \\ 0 \\ 0 \\ 0 \end{bmatrix} [D] \begin{bmatrix} A & 0 & 0 & 0 \end{bmatrix} \begin{pmatrix} U \\ \lambda_1 \\ \lambda_2 \\ \kappa \end{pmatrix} = \begin{pmatrix} P_C \\ 0 \\ 0 \\ 0 \end{pmatrix} + \begin{pmatrix} M \\ 0 \\ 0 \\ 0 \end{pmatrix} \{\delta\} \quad (41)$$

Parametric Linear System

Solution Set

Optimization
methods

Other
Methods

Interval
Methods

Comparison

Conclusions

I. Skalna, A method for outer interval solution of systems of linear equations depending linearly on interval parameters, *Reliable Computing*, 12, 2, 107-120, 2006.

Table I. Algorithm

$$R := \text{mid}(A([p]))^{-1};$$

$$\tilde{x} := R \cdot \text{mid}(b([p]));$$

$$[Z]_i = \sum_{j=1}^n R_{ij} \left(\omega(0, j) - \sum_{k=1}^n \tilde{x}_k \omega(j, k) \right)^T [p]$$

$$[D]_{ij} := \left(\sum_{\nu=1}^n R_{i\nu} \omega(\nu, j) \right)^T [p];$$

$$\text{outer} := \tilde{x} + [-1, 1] \langle [D] \rangle^{-1} |[Z]|$$

The use of diagonal matrix

Solution Set

Optimization
methods

Other
Methods

Interval
Methods

Comparison

Conclusions

A. Neumaier and A. Pownuk, Linear Systems with Large Uncertainties, with Applications to Truss Structures, Journal of Reliable Computing, 13(2), 149-172, 2007.

$$K = A^T * D * A$$

Element by element method

M. V. Rama Rao, R. L. Muhanna, and R. L. Mullen. Interval Finite Element Analysis of Thin Plates 7th International Workshop on Reliable Engineering Computing, At Ruhr University Bochum, Germany, 2016

$$[\mathbf{K}] = \begin{bmatrix} \mathbf{K}_1^{(e)} & & & \\ & \mathbf{K}_2^{(e)} & & \\ & & \mathbf{K}_3^{(e)} & \\ & & & \dots \end{bmatrix} = \begin{bmatrix} A_1^{(e)} & & & \\ & A_2^{(e)} & & \\ & & A_3^{(e)} & \\ & & & \dots \end{bmatrix} \begin{bmatrix} \text{diag}(\Lambda_1 \mathbf{a}_1) & & & \\ & \text{diag}(\Lambda_2 \mathbf{a}_2) & & \\ & & \text{diag}(\Lambda_3 \mathbf{a}_3) & \\ & & & \dots \end{bmatrix} \begin{bmatrix} A_1^T(e) \\ A_2^T(e) \\ A_3^T(e) \\ \dots \end{bmatrix} \quad (34)$$

This can be denoted as

$$[\mathbf{K}] = [\mathbf{A}][\mathbf{D}][\mathbf{A}]^T \quad (35)$$

Comparison between the different methods

$$\text{Comp.Complexity}(\text{Method1}) < \text{Comp.Complexity}(\text{Method2})$$

$$\text{Accuracy}(\text{Method1}) < \text{Accuracy}(\text{Method2})$$

Accuracy include also information about guaranteed accuracy.

$$\text{PossibleApplications}(\text{Method1}) < \text{PossibleApplications}(\text{Method2})$$

$$\text{Scalability}(\text{Method1}) < \text{Scalability}(\text{Method2})$$

Scalability include information about parallelization.

How to find the best method?

Example:

method 1: linearization

method 2: Monte Carlo

The problem is small

$$\text{EasyToImplement}(\text{Method1}) < \text{EasyToImplement}(\text{Method2})$$

$$\text{Accuracy}(\text{Method1}) < \text{Accuracy}(\text{Method2})$$

Better method is the method 2, i.e. the Monte Carlo method.

What to do in the conflict situations?

Example:

method 1: linearization

method 2: interval methods

$$\text{Comp.Complexity}(\text{Method1}) < \text{Comp.Complexity}(\text{Method2})$$

$$\text{Accuracy}(\text{Method1}) > \text{Accuracy}(\text{Method2})$$

If the main requirement is guaranteed solution,
then we can use the interval methods.

What to do in the conflict situations?

Example:

method 1: linearization

method 2: interval methods

$$\text{Comp.Complexity}(\text{Method1}) < \text{Comp.Complexity}(\text{Method2})$$

$$\text{Accuracy}(\text{Method1}) > \text{Accuracy}(\text{Method2})$$

If the problem is very large or nonlinear,
then it is not possible to apply the interval methods
and it is necessary to use linearization.

What to do in the conflict situations?

Linear model

Example:

method 1: m_1

method 2: m_2

Total score

$$\mu_1 = \sum_i w_i f_i(m_1)$$

$$\mu_2 = \sum_i w_i f_i(m_2)$$

If $\mu_1 > \mu_2$ then we need to pick the method 1.

If $\mu_1 < \mu_2$ then we need to pick the method 2.

What to do in the conflict situations?

Nonear model

Solution Set

Optimization
methods

Other
Methods

Interval
Methods

Comparison

Conclusions

Example:

method 1: m_1

method 2: m_2

Total score

$$\mu_1 = \Phi(f_1(m_1), f_2(m_1), \dots, f_k(m_1))$$

$$\mu_2 = \Phi(f_1(m_2), f_2(m_2), \dots, f_k(m_2))$$

If $\mu_1 > \mu_2$ then we need to pick the method 1.

If $\mu_1 < \mu_2$ then we need to pick the method 2.

or more generally

$$\Omega(f_1(m_1), \dots, f_k(m_1), f_1(m_2), \dots, f_k(m_2))) > 0$$

Conclusions

- Interval equations can be solved by using many different methods.
- Every method has some advantages and disadvantages.
- In order to choose the optimal method it is necessary to consider many different features of every computational method.