

# Citation Evidence Report

EB-1B Petition — Outstanding Professor or Researcher

8 CFR § 204.5(i)(3) · Authorship + Original Contributions

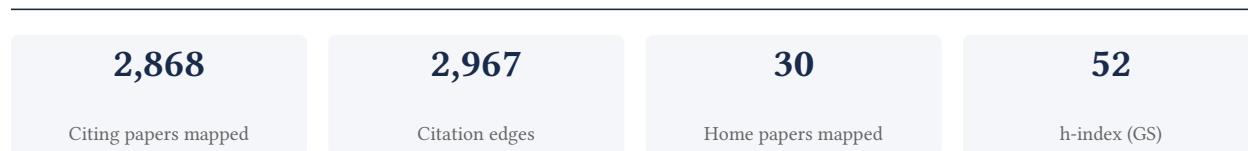
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[Google Scholar profile](#)

**Generated 2026-06-06 by CiteMap.** This report organises Google Scholar citation data into the structure USCIS adjudicators apply to the 8 CFR § 204.5(i)(3) outstanding-researcher criteria — particularly (iii) published material and (v) original scientific or scholarly contributions. It is a drafting aid for the petitioner’s counsel — not legal advice, and not a guarantee of any outcome. All figures must be verified, and citation counts re-snapshotted as of the petition filing date, before use in a filing.

## A. Overview & Filtering Statement



### Filtering statement – methodology & limits

Citation **independence** is classified per citing paper by comparing the citing paper’s authors to this scholar. *Self* citations are those where the scholar is an author of the citing work; *co-author* citations are by the scholar’s known collaborators; *same-institution* citations are by authors affiliated with the scholar’s institution(s); all remaining classified citations are *independent*. Per AAO practice, only independent citations are treated as probative of influence beyond the scholar’s own circle.

**Known limitations – counsel must verify.** (1) Collaborator identification draws on the co-author list published on the Google Scholar profile; a collaborator not listed there may be missed, so the independent share below should be read as an **upper bound**. (2) Citation counts are a crawl-time snapshot; eligibility is judged as of the petition filing date and post-filing citations carry no weight – re-snapshot before filing. (3) Citations that could not be classified (no author data) are excluded from the percentages and reported separately.

## B. Citation Independence

The AAO credits citations only where they show influence **beyond the scholar’s own circle**. Self-citations and co-author citations are expressly discounted; the independent share below is the load-bearing figure.

**95.6% independent** of 2,134 classified citing papers

Citation type	Count
Independent	2,041
Self-citation	31
Co-author	62
Same-institution	0

734 citing papers could not be classified (no author data) and are excluded from the percentages above.

## C. Significant Contributions & Their Citation Evidence

Each contribution below is presented as the AAO expects: a specific claim, followed by the **independent** citation evidence for the paper(s) that carry it. Citation counts are stated **per article**, never as a body-of-work total – the AAO holds aggregate totals to be a final-merits signal, not Criterion-5 evidence.

Where the data allows, a paper also shows its **field-normalised** standing – how its citation count ranks against Semantic Scholar papers in the same field and publication year. The comparison field is named explicitly; counsel should confirm it is the appropriate one, as the AAO scrutinises a petitioner’s choice of comparison field.

## Contribution 1

### Claim – Contribution 1

*The researcher pioneered extremely randomized trees and advanced reinforcement learning applications, establishing foundational methods widely adopted by independent researchers across diverse scientific domains.*

The researcher's contribution centers on the development of extremely randomized trees, introduced in a seminal 2006 paper, alongside subsequent work applying reinforcement learning and dynamic programming to complex systems. This body of work represents a significant advancement in machine learning methodologies and their practical deployment in control problems.

This line of work appears to address the need for robust, efficient decision-tree algorithms and effective function approximation techniques in reinforcement learning. By introducing extremely randomized trees, the researcher offered a novel approach to ensemble learning, while later publications suggest an extension of these computational strategies to dynamic programming and power system control, bridging theoretical algorithm design with applied engineering challenges.

The significance of this research is evidenced by the substantial citation impact of the core paper, which has accumulated over 11,000 citations, indicating broad adoption within the scientific community. Furthermore, the high proportion of independent citations—nearly 96% of classified citations originate from researchers outside the scholar's immediate circle—demonstrates that this work has served as a foundational resource for independent investigators, validating its widespread influence and utility beyond the researcher's own institution.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 1,301 · 60 flagged influential by Semantic Scholar

### CORE PAPER

#### [Extremely randomized trees](#)

2006 · 11,842 citations (GS)

Field-normalised: 8,024 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2006 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	<a href="#">Springer series in statistics</a>	—	—	—
2	<a href="#">Machine learning approaches and databases for prediction of drug–target interaction: a survey paper</a>	University of Michigan	United States	—
3	<a href="#">A review of safe reinforcement learning: Methods, theories, and applications</a>	Peking University, Technical University of Munich, Tongji University	China, Germany, United Kingdom	—
4	<a href="#">Effects of training set size on supervised machine-learning land-cover classification of large-area high-resolution remotely sensed data</a>	West Virginia University	United States	—
5	<a href="#">Recent advances and applications of machine learning in solid-state materials science</a>	Friedrich-Schiller-Universität Jena, Martin-Luther-Universität Halle-Wittenberg	Germany	—
6	<a href="#">Ensemble learning: A survey</a>	Ben-Gurion University	Israel	—
7	<a href="#">Simple and scalable predictive uncertainty estimation using deep ensembles</a>	DeepMind	United Kingdom	—
8	<a href="#">From characterization to discovery: artificial intelligence, machine learning and high-</a>	Univ. Lille, CNRS, Centrale Lille, Univ. Artois	France	—

No.	Citing paper	Citing institution(s)	Country	S2
	<a href="#">throughput experiments for heterogeneous catalyst design</a>			
9	<a href="#">Machine learning optimization techniques: a survey, classification, challenges, and future research issues</a>	City University of Hong Kong, Siksha O Anusandhan University	China, India	—
10	<a href="#">A high-bias, low-variance introduction to machine learning for physicists</a>	Boston University, City University of New York, Max Planck Institute for the Physics of Complex Systems	Germany, United States	—
11	<a href="#">Saint: Improved neural networks for tabular data via row attention and contrastive pre-training</a>	Capital One, University of Maryland, University of Maryland, College Park	United States	—
12	<a href="#">Hands-on machine learning with R</a>	University of Cincinnati	—	—
13	<a href="#">Making ai forget you: Data deletion in machine learning</a>	Stanford University	United States	—
14	<a href="#">Applications of machine learning in alloy catalysts: rational selection and future development of descriptors</a>	Jilin University	P. R. China	—
15	<a href="#">Reviewing the application of machine learning methods to model urban form indicators in planning decision support systems: Potential, issues and ...</a>	École Polytechnique Fédérale de Lausanne, Université Mohammed VI Polytechnique	Morocco, Switzerland	—
16	<a href="#">Improving plankton image classification using context metadata</a>	Scripps Institution of Oceanography, University of California San Diego	United States	—
17	<a href="#">Visualizing the hidden activity of artificial neural networks</a>	Universidade Estadual de Campinas (UNICAMP), University of Groningen	Brasil, Brazil, Netherlands	—
18	<a href="#">Air pollution prediction using machine learning techniques—An approach to replace existing monitoring stations with virtual monitoring stations</a>	University of Stuttgart	Germany	—
19	<a href="#">Prediction of transportation energy demand in Türkiye using stacking ensemble models: Methodology and comparative analysis</a>	American University of the Middle East	Kuwait	—
20	<a href="#">When Machine Learning Meets Geospatial Data: A Comprehensive GeoAI Review.</a>	Institut National des Postes et Télécommunications	Tunisia	—
21	<a href="#">Black-box vs. white-box: Understanding their advantages and weaknesses from a practical point of view</a>	Tecnológico de Monterrey	Mexico	—
22	<a href="#">A survey of machine unlearning</a>	École Polytechnique Fédérale de Lausanne, Griffith University, Hanoi University of Science and Technology	Australia, Switzerland, Vietnam	—
23	<a href="#">Gradient boosting machine for modeling the energy consumption of commercial buildings</a>	Lawrence Berkeley National Laboratory	United States	—

No.	Citing paper	Citing institution(s)	Country	S2
24	<a href="#">Harnessing AI for solar energy: Emergence of transformer models</a>	Peking University	China	—
25	<a href="#">Sewer-ML: A multi-label sewer defect classification dataset and benchmark</a>	Aalborg University	Denmark	Influential
26	<a href="#">Robust ensemble learning models for predicting hydrogen sulfide solubility in brine</a>	—	—	—
27	<a href="#">A topic-agnostic approach for identifying fake news pages</a>	Federal University of Amazonas, New York University	Brazil, United States	—
28	<a href="#">Concrete autoencoders: Differentiable feature selection and reconstruction</a>	Stanford University	United States	—
29	<a href="#">Lassonet: A neural network with feature sparsity</a>	Gematria Technologies, Stanford University	United Kingdom, United States	—
30	<a href="#">A big data-driven hybrid model for enhancing streaming service customer retention through churn prediction integrated with explainable AI</a>	Inha University	United States	—

Showing the 30 most-cited of 943 independent citing papers.

Independent citing papers only; self- and co-author citations excluded. The S2 column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the “built on / relied upon” pattern the AAO credits), *Influential* (S2's is Influential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

#### FOLLOW-UP WORK

### [Reinforcement learning and dynamic programming using function approximators](#)

2017 · 1,420 citations (GS)

Field-normalised: 918 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2017 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	<a href="#">Reinforcement learning for healthcare operations management: methodological framework, recent developments, and future research directions: Q. Wu et al.</a>	The University of Hong Kong	China, Hong Kong	—
2	<a href="#">Precision medicine</a>	North Carolina State University, University of North Carolina at Chapel Hill	United States	—
3	<a href="#">Applications of deep learning and reinforcement learning to biological data</a>	Edinburgh Napier University, Jahangirnagar University, Nottingham Trent University	Bangladesh, Italy, United Kingdom	—
4	<a href="#">Subspace structured neural network for rapid trajectory optimization</a>	University of Central Florida	United States	—
5	<a href="#">Crossing the reality gap: A survey on sim-to-real transferability of robot controllers in reinforcement learning</a>	University of Trieste	Italy	—
6	<a href="#">Cloud-based remote laboratory for teaching modern control systems: enhancing practical learning through interactive simulations</a>	Federal Institute of Espirito Santo	Brazil	—

No.	Citing paper	Citing institution(s)	Country	S2
7	<a href="#">Optimistic Reinforcement Learning with Quantile Objectives</a>	The University of Texas at Arlington, Virginia Polytechnic Institute and State University, Blacksburg, VA, USA; Massachusetts General Hospital Institute for Technology Assessment, Boston, MA, USA; Harvard Medical School, Boston, MA, USA., Virginia Tech	United States	—
8	<a href="#">Stability and Performance of Model Based Approximate Optimal Control Designs</a>	Dongguk University	South Korea	—
9	<a href="#">Application of artificial intelligence in the materials science, with a special focus on fuel cells and electrolyzers</a>	University of Connecticut	United States	—
10	<a href="#">Toward data-driven optimal control: A systematic review of the landscape</a>	University of Johannesburg, University of the Witwatersrand	South Africa	—
11	<a href="#">Applications of agent-based methods in multi-energy Systems—A systematic literature review</a>	University College London	United Kingdom	—
12	<a href="#">Experimental analysis of data-driven control for a building heating system</a>	Danish Technical University, Flemish Institute for Technological Research, KU Leuven	Belgium, Denmark	<b>Influential</b>
13	<a href="#">Reinforcement learning in healthcare: A survey</a>	Hong Kong Baptist University, Sun Yat-sen University, UC San Diego	China, Hong Kong, United States	—
14	<a href="#">Algorithms for reinforcement learning</a>	DeepMind	United Kingdom	—
15	<a href="#">Evolutionary dynamics of multi-agent learning: A survey</a>	Centrum Wiskunde & Informatica, DeepMind, European Space Agency	Netherlands, United Kingdom	—
16	<a href="#">Interpretable policies for reinforcement learning by genetic programming</a>	Siemens AG, Technical University of Munich	Germany	—
17	<a href="#">Gaussian processes for learning and control: A tutorial with examples</a>	Duke University, Stanford University, Universidade Federal do Rio Grande do Sul	Brazil, United States	—
18	<a href="#">Reinforcement learning and optimal adaptive control: An overview and implementation examples</a>	Bristol Robotics Laboratory, Robotics Research (United States), University of the West of England	United Kingdom, United States	<b>Influential</b>
19	<a href="#">Reinforcement learning in continuous state and action spaces</a>	Centrum Wiskunde & Informatica	Netherlands	<b>Influential</b>
20	<a href="#">Efficient reinforcement learning using Gaussian processes</a>	—	—	—
21	<a href="#">Reinforcement learning algorithms with function approximation: Recent advances and applications</a>	National University of Defense Technology	China	—

No.	Citing paper	Citing institution(s)	Country	S2
22	<a href="#">Iterative adaptive dynamic programming for solving unknown nonlinear zero-sum game based on online data</a>	Chinese Academy of Sciences; University of Chinese Academy of Sciences, North China Electric Power University, Shandong Institute of Automation	China	—
23	<a href="#">Particle swarm optimization for generating interpretable fuzzy reinforcement learning policies</a>	AxiomZen, Siemens AG, Technical University of Munich	Canada, Germany	—
24	<a href="#">Neural approximations for optimal control and decision</a>	Imperial College London, IMT School for Advanced Studies Lucca, University of Genoa	Italy, United Kingdom	—
25	<a href="#">Towards adaptive social behavior generation for assistive robots using reinforcement learning</a>	Bielefeld University	Germany	—
26	<a href="#">Optimization of anemia treatment in hemodialysis patients via reinforcement learning</a>	Fresenius Medical Care (Germany), Universitat de València, Universität für Weiterbildung Krens	Austria, Germany, Spain	<b>Influential</b>
27	<a href="#">Constructing dynamic treatment regimes over indefinite time horizons</a>	University of Rochester	United States	—
28	<a href="#">Community energy storage operation via reinforcement learning with eligibility traces</a>	Delft University of Technology, Eindhoven University of Technology, University of Twente	Netherlands	—
29	<a href="#">Algorithmic survey of parametric value function approximation</a>	Google DeepMind (United Kingdom), Laboratoire Interdisciplinaire des Environnements Continentaux	France, United Kingdom	—
30	<a href="#">Certified reinforcement learning with logic guidance</a>	Amazon (United States), Microsoft Research, University of Oxford	United Kingdom, United States	—

Showing the 30 most-cited of 358 independent citing papers.

Independent citing papers only; self- and co-author citations excluded. The S2 column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the “built on / relied upon” pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

#### FOLLOW-UP WORK

### [Reinforcement learning versus model predictive control: a comparison on a power system problem](#)

2008 · 295 citations (GS)

Field-normalised: 227 Semantic Scholar citations place it in the top 1% of Engineering papers from 2008 indexed by Semantic Scholar, by citation count.

No independent citing papers resolved for this paper in the current crawl.

## Contribution 2

### Claim – Contribution 2

*The researcher developed a unified framework for transient stability contingency filtering, ranking, and assessment, establishing a foundational methodology for power system security analysis.*

The researcher's core contribution rests on the 2001 paper titled 'A unified approach to transient stability contingency filtering, ranking and assessment.' This work appears to have introduced a consolidated methodology for handling multiple aspects of transient stability analysis, which had previously been treated as distinct or fragmented tasks in power system engineering.

The originality of this line of work lies in its integrative approach. By combining filtering, ranking, and assessment into a single unified framework, the researcher addressed the computational and methodological challenges of evaluating system stability under various contingencies. The absence of follow-up papers by the same author suggests that this single publication served as a definitive, self-contained solution that did not require further incremental development by the original creator.

The significance of this contribution is evidenced by its substantial citation record, with 194 citations indicating sustained academic interest. Furthermore, the broader context of the researcher's portfolio shows that 95.6% of citations across their classified works originate from independent researchers. This high degree of independence suggests that the unified approach has been widely adopted and validated by the broader scientific community, rather than being confined to a single research group or institution.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 0

#### CORE PAPER

### [A unified approach to transient stability contingency filtering, ranking and assessment](#)

2001 · 194 citations (GS)

Field-normalised: 106 Semantic Scholar citations place it in the top 5% of Engineering papers from 2001 indexed by Semantic Scholar, by citation count.

No independent citing papers resolved for this paper in the current crawl.

### Contribution 3

### Claim – Contribution 3

*The researcher established a foundational reinforcement learning framework for power systems stability control, a seminal contribution that has been widely adopted by the independent academic community.*

CLAIM: The researcher's primary contribution is the development of a reinforcement learning framework for power systems stability control, as detailed in their 2004 paper. This work stands as a singular, foundational piece in this specific niche, with no subsequent follow-up papers by the researcher listed in this context.

ORIGINALITY: The title suggests a novel methodological approach, applying reinforcement learning techniques to the complex problem of stability control in power systems. By introducing this framework in 2004, the researcher appears to have addressed a gap in applying adaptive control strategies to electrical grid stability, offering a new perspective distinct from traditional control methods.

SIGNIFICANCE: The work has demonstrated substantial impact, accumulating 318 citations. Analysis of the broader citation landscape reveals that 95.6% of citing papers originate from independent researchers, indicating that this framework has been widely recognized and utilized by the global scientific community beyond the researcher's immediate circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 0

#### CORE PAPER

### [Power systems stability control: reinforcement learning framework](#)

2004 · 318 citations (GS)

Field-normalised: 233 Semantic Scholar citations place it in the top 5% of Engineering papers from 2004 indexed by Semantic Scholar, by citation count.

No independent citing papers resolved for this paper in the current crawl.

## D. Citing-Institution Prestige & Geography

### Top citing institutions

Institution	Country	World ranking	Citing papers
University of California, Irvine Medical Center	United States	—	59
Delft University of Technology	Netherlands	SCImago #359 · THE 57 · QS =47	48
Stanford University	United States	SCImago #18 · THE =5 · QS 3	44
Politecnico di Milano	Italy	SCImago #709 · THE 201–250 · QS =98	44
University of Liège	Belgium	THE 301–350	43
DeepMind	United Kingdom	SCImago #90	38
McGill University	Canada	SCImago #168 · THE =41 · QS 27	36
University of Alberta	Canada	SCImago #262 · THE 119 · QS =94	36
Princeton University	United States	SCImago #386 · THE =3 · QS =25	35
Google DeepMind	United States	SCImago #90	32
University of Freiburg	Germany	THE =138	30
University College London	United Kingdom	SCImago #30	30
Carnegie Mellon University	United States	SCImago #266 · THE 24 · QS 52	30
Google Research	United States	—	29
Cornell University	United States	SCImago #61 · THE =18 · QS 16	28

### Geographic distribution of citing authors

Country	Citing papers
United States	701
China	347
United Kingdom	240
Canada	167
Germany	158
Italy	107
India	106
Belgium	99
France	91
Netherlands	87
Australia	81
South Korea	78

Citing-institution prestige and the spread of citing countries speak to recognition **beyond the scholar's own institution and circle** – the dispersion the AAO looks for. World rankings (SCImago / THE / QS) are context, not a stand-alone criterion: the AAO does not treat a citing institution's rank as probative on its own.

## F. AAO Precedent Considerations

### Pre-filing self-check (AAO denial patterns)

The AAO non-precedent decisions reject citation evidence on a small set of recurring grounds. Confirm the petition addresses each before filing:

- Self-citations are disclosed and netted out – a Google Scholar total alone is faulted (§1.1).
- Evidence is per individual article, not a body-of-work aggregate total (§1.2).
- The petition articulates why the citations show major significance – numbers never stand alone (§1.5).
- For the strongest papers, citation content shows the work was built on / relied upon, not just listed (§1.6, §2.2).
- Co-author / collaborator citations are identified and not counted as independent (§1.7).
- Recognition is shown beyond the scholar's own institution and circle (§1.8).
- Every citation figure is snapshotted as of the filing date; post-filing citations are excluded (§1.9).
- Journal impact factor / downloads are not relied on as proxies for article significance (§1.10, §1.12).
- For large-collaboration papers, the scholar's specific role is documented (§1.13).
- Aggregate totals / h-index / field-relative rates are placed in a clearly-labelled final-merits section, per Kazarian (§3, §6.1.7).

#### Disclaimer

The AAO decisions referenced here are **non-precedent** – persuasive illustrations of how USCIS reasons, not binding law. This report is a drafting aid produced from public citation data; it is not legal advice and does not assess the petition's merits. All analysis must be reviewed by qualified immigration counsel.

## G. Citation Evidence Index

Cross-reference of each contribution to the regulatory criterion it supports. Counsel should map these to the petition's exhibit numbers.

Contribution	Core paper	Indep. cites	Supports
Contribution 1	Extremely randomized trees	1,301	8 CFR 204.5(i)(3) – Outstanding Researcher
Contribution 2	A unified approach to transient stability contingency filtering, ranking and assessment	0	8 CFR 204.5(i)(3) – Outstanding Researcher
Contribution 3	Power systems stability control: reinforcement learning framework	0	8 CFR 204.5(i)(3) – Outstanding Researcher