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[Karl Aberer](#)

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Karl Aberer is a full professor for Distributed Information Systems at EPFL Lausanne, Switzerland, since 2000; from 2005 to 2012 the director of the Swiss National Research Center for Mobile Information and Communication Systems (NCCR-MICS, www.mics.ch); since September 2012 he is Vice-President of EPFL responsible for information systems; member of the editorial boards of VLDB Journal, ACM Transaction on Autonomous and Adaptive Systems and World Wide Web Journal.

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[View author feedback](#) of Houston and Texas Medical Center in developing neural interfaces for rehabilitation. He is currently an Assistant Professor at Robotics Department, Nazarbayev University, Kazakhstan. His research focuses on machine learning algorithms, neural signal processing and Brain-Computer/Machine Interfaces.

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**Wasif Afzal**Mälardalen University

Professor in Computer Science at Mälardalen University, Sweden, specialising in research areas such as software testing, software quality, software metrics and empirical software engineering in general.

Software Engineering**Giuseppe Agapito**University "Magna Graecia" of Catanzaro

Giuseppe Agapito is an Assistant Professor and a senior research scientist in the field of Parallel and Distributed Computing, Machine Learning and Graph Theory at the University Magna Græcia, Catanzaro. His research interests focus on the study of machine learning methods that can be used to take advantage of the vast amount of data that are produced nowadays. In particular, the research focuses on the development, implementation, and application of computational intelligence techniques for addressing complex real-world problems in different domains, especially in the field of biology and omics sciences.

Giuseppe Agapito has published his research in various top-quality academic outlets, with more than 100 papers in international journals and conference proceedings. He serves as a reviewer for several scientific journals and a chair or program committee member of several national and international conferences.

Bioinformatics Computational Science Data Mining & Machine Learning Distributed & Parallel Computing GenomicsNetwork Science & Online Social Networks**Rajeev Agrawal**North Carolina A & T State University

Assistant Professor in the department of computer systems technology at North Carolina A & T State University. Research interests: Big data Analytics, Cloud Computing, Topic Modelling, and Geo Spatial information systems. Member of IEEE, ACM, and ASEE. Published more than 50 referred journal and conference papers and 4 book chapters.

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Ayaz Ahmad

COMSATS University Islamabad - Wah Campus

Ayaz Ahmad is currently serving as Assistant Professor in the Department of Electrical and Computer Engineering, COMSATS University Islamabad - Wah Campus, Wah Cantt., Pakistan. He obtained his MS and Ph.D. degrees both in Telecommunication from Ecole Supérieure d'Electricité (Supelec), Gif-sur-Yvette, France, in 2008 and 2011, respectively. He obtained his B.Sc. in Electrical Engineering from University of Engineering and Technology, Peshawar, Pakistan in 2006. From 2006 to 2007, he was a faculty member at the Department of Electrical Engineering, FAST-NUCES, Peshawar, Pakistan. Ayaz has several years of research experience and has authored/coauthored several scientific publications in various refereed international journals and conferences. He has also published several book chapters and is the leading co-editor of the book entitled, "Smart Grid as a Solution for Renewable and Efficient Energy" published in 2016. He is currently an Associate Editor with IEEE Access, and Springer Human-centric Computing and Information Sciences. He has also served as the guest editor of two special issues for IEEE Access. He is Senior Member of IEEE. His research interests include resource allocation in wireless communication systems, energy management in smart grid, and application of optimization methods to engineering problems.

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Ghufran Ahmad

National University of Sciences and Technology (NUST), Islamabad, Pakistan

Ghufran Ahmad's research focuses on microeconomic theory specifically dealing with resource allocation, social choice and matching problems. He is currently working as an Assistant Professor at NUST Business School, Pakistan.

He received his B.Sc. (Hons) in Economics from Lahore University of Management Sciences, Pakistan in 2012. After that, he joined Texas A&M University in College Station, TX, USA to pursue his Ph.D. in Economics, completing it in 2017 under the supervision of Dr. Guoqiang Tian and Dr. Vikram Manjunath.

Agents & Multi-Agent Systems Neural Networks Optimization Theory & Computation Sentiment Analysis



Irfan Ahmad

King Fahad University of Petroleum and Minerals

Dr. Irfan Ahmad is an Assistant Professor in Information and Computer Science department at King Fahd University of Petroleum and Minerals (KFUPM), Dhahran, Saudi Arabia. He received his PhD in Computer Science from TU Dortmund, Germany in 2017.

Dr. Ahmad's research interests are in the areas of pattern recognition especially in document-image analysis, handwriting recognition, and machine-printed text recognition. In addition, he is also interested in machine learning and

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Imran Ahmed

Institute of Technology and Management

Dr. Imran Ahmed is an Associate Professor at the Institute of Management Sciences (IMSciences) in Pakistan. He received his PhD (Computer Science) from the University of Southampton, UK and has extensive teaching and research experience.

Dr. Ahmed's primary research interests include Data Science, Machine Learning, Computer Vision and Image Processing.

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Sedat Akleylek

University of Tartu

Sedat Akleylek received the B.Sc. degree in Mathematics majored in Computer Science from Ege University in 2004 in Izmir, Turkey, M.Sc. and Ph.D. degrees in Cryptography from Middle East Technical University in 2008 and 2010, in Ankara, Turkey, respectively. He was a post-doctoral researcher at Cryptography and Computer Algebra Group, TU Darmstadt, Germany between 2014-2015. He is currently employed as a professor at the Department of Computer Engineering, Ondokuz Mayıs University, Samsun, Turkey since 2022. He is a member of Chair of Security and Theoretical Computer Science, University of Tartu, Tartu, Estonia. He is a member of the editorial board of IEEE Access, Turkish Journal of Electrical Engineering and Computer Sciences, PeerJ Computer Science, and International Journal of Information Security Science. He is co-chair of IEEE Turkey Blockchain Group. His research interests include the areas of post-quantum cryptography, algorithms and complexity, architectures for computations in finite fields, blockchain, applied cryptography for cyber security, malware analysis, IoT and fog computing. He has published more than 100 research papers in international journals, conference proceedings, book chapters and has solved several real-world security and data analytics problems for the industry.

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[**Tawfik Al-Hadhrami**](#)

[Nottingham Trent University](#)

Tawfik Al-Hadhrami is currently working as a Senior Lecturer at Nottingham Trent University, UK. He received his MSc degree in IT/Applied System Engineering from Heriot-Watt University, Edinburgh, United Kingdom. He received his PhD degree in Mesh Communication and IoT from the University of the West of Scotland, Glasgow, UK, 2015. He was involved in research at the University of the West of Scotland, Networking Group. He is an Associate Editor for IEEE Access, PeerJ computer Science, Frontiers in Communications and Networks (IoT and Sensor Networks) and International Journal of Cyber Forensics and Advance Threat Investigations journals. His research interest includes the Internet of Things (IoT) and Applications, Data Science, Network Infrastructures & Emerging Technologies, Artificial Intelligence, Computational Intelligence and 5/6G Wireless Communications. He has established collaboration with the different international institutions over the world. He is a member of the Network Infrastructure and Cyber Security group (NICS) at NTU. He is involved in different projects with industries.

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[**Vicente Alarcon-Aquino**](#)

[Universidad de las Americas Puebla](#)

Vicente Alarcon-Aquino received his Ph.D. and D.I.C. degrees in Electrical and Electronic Engineering from Imperial College London, London, U.K. in 2003. He is currently a full Professor and former department head in the department of computing, electronics, and mechatronics at the Universidad de las Americas Puebla, Mexico. In 2017, he spent a short term research stay as a Visiting Senior Research Fellow in the Department of Informatics at King's College London, UK. He has authored over 180 research articles in several refereed journals and conference proceedings, has written a book on MPLS networks, and has several citations to his research articles. He has served as Guest Editor for the Journal of Universal Computer Science, and is currently acting as an Associate Editor for IEEE Access Journal and as an Academic Editor for PeerJ Computer Science. He is a Senior Member of IEEE, belongs to the Mexican National System of Researchers, and has been elected to membership of the Mexican Academy of Sciences. His current research interests include cybersecurity, network monitoring, anomaly detection, wavelet analysis, and machine learning.

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A member of the ACM, the Information Processing Society of Japan, and IBM Academy of Technology. She has been supporting accessibility related open standards efforts, and 2010 she served as a co-general chair for the international conference for Web accessibility (W4A). She was inducted into the Women in Technology International (WITI) Hall of Fame in 2003, and she has been actively working to help women engineers pursue technical careers. Chieko was appointed to IBM Fellow in 2009.

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Grady Booch

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Grady is recognized for his innovative work in software engineering. Grady is an IBM Fellow and has also been given the honor of Fellow for the Association for Computing Machinery and the Institute of Electrical and Electronics Engineers. He has been awarded the Lovelace Medal and has given the Turing Lecture on behalf of the British Computer Society. Author of six best-selling books, Grady has published hundreds of technical articles and has lectured extensively around the world.

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Christine L Borgman

University of California, Los Angeles

Christine L. Borgman, Professor & Presidential Chair in Information Studies at UCLA, is the author Big Data, Little Data No Data (2015), Scholarship in the Digital Age (2007) and From Gutenberg to the Global Information Infrastructure (2000), and about 200 other publications in information studies, computer science, and communication. She is a Fellow of the ACM and of AAAS; and a member of the Board of Directors of the Electronic Privacy Information Center.

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Vinton Cerf

Google

Cerf is the co-designer of the TCP/IP protocols and the architecture of the Internet. He is the past President of ACM and a member of the National Science Board.

Cerf has received the US Presidential Medal of Freedom, US National Medal of Technology, the Queen Elizabeth Prize for Engineering, the Prince of Asturias Award, the Tunisian National Medal of Science, the Japan Prize, the Charles Stark Draper award, the ACM Turing Award, the Legion d'Honneur and 24 honorary degrees.

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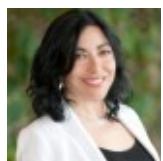


Krishnendu Chakrabarty

Duke University

Current research is focused on testing & design-for-testability of integrated circuits; digital microfluidics, biochips, & cyberphysical systems; optimization of digital print and production system infrastructure. Currently an ACM Distinguished Speaker & has been a Distinguished Visitor of the IEEE Computer Society. Recipient of many awards, including the Humboldt Research Award. Editor-in-Chief of ACM Journal on Emerging Technologies in Computing Systems and IEEE Transactions on VLSI Systems.

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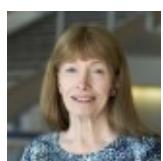


Jennifer T Chayes

Microsoft Research New England

Chayes is a leader in the field of network science, with applications in computer science, economics, biology and math. She is founder and Managing Director of Microsoft Research New England and NYC, and was previously Professor of Math at UCLA. She received an NSF Postdoctoral Fellowship, a Sloan Fellowship and the ABI Women of Vision Leadership Award. She was a member of the IAS Princeton, is a Fellow of the AAAS, ACM, AMS and is an elected member of the American Academy of Arts and Sciences.

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Professor Emerita of Electrical Engineering & Computer Science, University of Michigan. Architect and principal author of the landmark 'Mead-Conway' text, "Introduction to VLSI Systems". Pioneering innovator of the digital e-commerce "fabless-design + silicon-foundry" microelectronics ecosystem. Elected Fellow, IEEE. Elected Member, NAE. Hon. Degrees, Trinity College and Illinois Institute of Technology. Wetherill Medal, Franklin Institute. James Clerk Maxwell Medal, IEEE.

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[Carnegie Mellon University](#)

Lorrie Faith Cranor is the Director and Bosch Distinguished Professor of the CyLab Security and Privacy Institute and FORE Systems Professor of Computer Science and of Engineering and Public Policy at Carnegie Mellon University. She also directs the CyLab Usable Privacy and Security Laboratory (CUPS) and co-directs the MSIT-Privacy Engineering masters program. In 2016 she served as Chief Technologist at the US Federal Trade Commission. She co-founded Wombat Security Technologies, a security awareness training company that was acquired by Proofpoint. She is a fellow of the ACM and IEEE and a member of the ACM CHI Academy.

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[**Peter Denning**](#)

[Naval Postgraduate School](#)

Distinguished professor of computer science at Naval Postgraduate School. Past president of ACM. Past editor in chief of Communications of ACM. Currently editor of ACM Ubiquity. Author of ten books, most recent Great Principles of Computing (MIT Press 2015). Author of over four hundred scientific papers and articles.

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[**Ian Foster**](#)

[Argonne National Laboratory](#)

I am a computer scientist with a predilection for building software systems (and, more recently, for deploying services) that solve problems in the sciences. I am a Distinguished Fellow at Argonne National Laboratory and a Professor at the University of Chicago. I am affiliated, in particular, with the Department of Computer Science, Data Science and Learning Division, and Institute for Molecular Engineering.

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[**Martin Fowler**](#)

[ThoughtWorks](#)

I am an author, speaker... essentially a loud-mouthed pundit on the topic of software development. I work for ThoughtWorks, a software delivery company, where I have the exceedingly inappropriate title of "Chief Scientist". I've written half-a-dozen books on software development, including Refactoring and Patterns of Enterprise Application Architecture. I write regularly about software development on martinfowler.com

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[**Yolanda Gil**](#)

[University of Southern California](#)

Dr. Yolanda Gil is Director of Knowledge Technologies and Associate Division Director at the Information Sciences Institute of the University of Southern California, and Research Professor in Computer Science and in Spatial Sciences. She is also Associate Director of Interdisciplinary Programs in Informatics. She received her M.S. and Ph. D. degrees in Computer Science from Carnegie Mellon University, with a focus on artificial intelligence. Her research is on intelligent interfaces for knowledge capture and discovery, which she investigates in a variety of projects concerning knowledge-based planning and problem solving, information analysis and assessment of trust, semantic annotation and metadata, and community-wide development of knowledge bases. Dr. Gil collaborates with scientists in different domains on semantic workflows and metadata capture, social knowledge collection, computer-mediated collaboration, and automated discovery. Dr. Gil has served in the Advisory Committee of the Computer Science and Engineering Directorate of the National Science Foundation. She initiated and chaired the W3C Provenance Group that led to a community standard in this area. Dr. Gil is a Fellow of the Association for Computing Machinery (ACM), and Past Chair of its Special Interest Group in Artificial Intelligence. She is also Fellow of the Association for the Advancement of Artificial Intelligence (AAAI), and was elected as its 24th President in 2016.

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[**Wendy Hall**](#)

[University of Southampton](#)

Wendy Hall, DBE, FRS, FREng, is Professor of Computer Science in Electronics and Computer Science, University of Southampton, and is a Director of the Web Science Institute. She was Head of the School of Electronics and Computer Science (ECS) from 2002 to 2007, and was Dean of the Faculty of Physical Sciences and Engineering from 2010 to 2014.

One of the first computer scientists to undertake serious research in multimedia and hypermedia, she has been at its forefront ever since. The influence of her work has been significant in many areas including digital libraries, the

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She was elected President of the Association for Computing Machinery (ACM) in July 2008, and was the first person from outside North America to hold this position.

Until July 2008, she was Senior Vice President of the Royal Academy of Engineering, was a member of the UK Prime Minister's Council for Science and Technology, and was a founder member of the Scientific Council of the European Research Council. She was President of the British Computer Society from 2003 to 2004 and an EPSRC Senior Research Fellow from 1996 to 2002.

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[**James Hendler**](#)

[Rensselaer Polytechnic Institute](#)

Director of the Institute for Data Exploration and Applications and the Tetherless World Professor of Computer, Web and Cognitive Sciences at RPI. He is a Fellow of the AAAI, the BCS, the IEEE and the AAAS. He is the former Chief Scientist of the Information Systems Office at the US Defense Advanced Research Projects Agency (DARPA), and was the first computer scientist to serve on the Board of Reviewing editors for Science.

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[**Lydia E Kavraki**](#)

[Rice University](#)

Lydia Kavraki received her B.A. in Computer Science from the University of Crete in Greece and her Ph.D. in Computer Science from Stanford University. Her research contributions are in physical algorithms and their applications in robotics as well as in computational structural biology and biomedicine. Kavraki is the recipient of the ACM Grace Murray Hopper Award; a Fellow of ACM, IEEE, AAAS, AAAI, and AIMBE; and a member of the Institute of Medicine of the National Academies.

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[Pattie Maes](#)

[MIT](#)

Pattie Maes is the Alexander W. Dreyfoos (1954) Professor at MIT's Media Laboratory and the academic head for the Program in Media Arts and Sciences. She directs the Media Lab's Fluid Interfaces research group, whose goal is to design and develop computer interfaces that are a more natural extension of our minds, bodies and behavior. She holds bachelor's and PhD degrees in computer science from the Vrije Universiteit Brussel in Belgium.

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[Kurt Mehlhorn](#)

[Max Planck Institute for Informatics](#)

Kurt Mehlhorn is Director at the Max Planck Institute for Informatics.

[Algorithms & Analysis of Algorithms Optimization Theory & Computation Theory & Formal Methods](#)



[David Patterson](#)

[UC Berkeley](#)

The Pardee Professor of Computer Science, UC Berkeley; Past Chair, CS Division; Past Chair, Computing Research Association; Past President, Association for Computing Machinery. Best known projects are Reduced Instruction Set Computers, Redundant Arrays of Inexpensive Disks, and Network of Workstations. All helped lead to multibillion-dollar industries. Elected Fellow, National Academy of Engineering, National Academy of Sciences, Computer History Museum; IEEE von Neumann Medal; NEC C&C Prize .

[Computer Architecture](#)



[Radia Perlman](#)

[Dell EMC](#)

Inventor of innovations that make today's network protocols scalable, robust, and self-organizing. In particular, link state routing, spanning tree, and TRILL. Also, innovations in security including distributed algorithms resilient against

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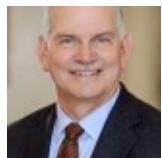
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- Internet Hall of Fame induction (2014)
- SIGCOMM Award (2010)
- USENIX Lifetime Achievement Award (2006)
- Recipient of the first Anita Borg Institute Women of Vision Award for Innovation in 2005
- Silicon Valley Intellectual Property Law Association Inventor of the year (2003)
- Honorary Doctorate, Royal Institute of Technology (June 28, 2000)
- Twice named as one of the 20 most influential people in the industry by Data Communications magazine: in the 20th anniversary issue (1992) and the 25th anniversary issue (1997). Perlman is the only person to be named in both issues
- Fellow of the Association for Computing Machinery, class of 2016

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[**H. Vincent Poor**](#)

[Princeton University](#)

The Michael Henry Strater University Professor, and Dean of Engineering and Applied Science, Princeton University. Research interests in information theory, stochastic analysis and statistical signal processing, with applications in wireless networks and related fields, including social networks and smart grid. Member NAE & NAS; Foreign Member of the Royal Society; Fellow, American Academy of Arts & Sciences.

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[**Steven Salzberg**](#)

[Johns Hopkins University](#)

Steven Salzberg is a Bloomberg Distinguished Professor of Biomedical Engineering, Computer Science, and Biostatistics at Johns Hopkins University, and the Director of the Center for Computational Biology. His research focuses on the development of novel computational methods for analysis of DNA from the latest sequencing technologies. His software has been downloaded >1,000,000 times and he writes a popular science blog at Forbes magazine. He's an elected Fellow of AAAS and ISCB.

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[Henning Schulzrinne](#)

[Columbia University](#)

Prof. Henning Schulzrinne, Levi Professor of Computer Science at Columbia University, received his Ph.D. from the University of Massachusetts in Amherst, Massachusetts. MTS at AT&T Bell Laboratories; associate department head at GMD-Fokus (Berlin), before joining the Computer Science and EE departments at Columbia University. He served as chair of Computer Science from 2004 to 2009 and as Chief Technology Officer of the Federal Communications Commission (FCC) from 2012 until 2014.

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[Margo Seltzer](#)

[University of British Columbia](#)

Margo Seltzer the Canada 150 Research Chair in Computer Systems and the Cheriton Family chair in Computer Science at The University of British Columbia. Her research interests are in systems, construed quite broadly: systems for capturing and accessing data provenance, file systems, databases, transaction processing systems, storage and analysis of graph-structured data, new architectures for parallelizing execution, and systems that apply technology to problems in healthcare.

Dr. Seltzer was a co-founder and CTO of Sleepycat Software, the makers of Berkeley DB, recipient of the 2020 ACM SIGMOD Systems Award.

She serves on Advisory Council for the Canadian COVID alert app and the Computer Science and Telecommunications Board (CSTB) of the (US) National Academies.

She is a past President of the USENIX Association and served as the USENIX representative to the Computing Research Association Board of Directors and on the Computing Community Consortium.

She is a member of the National Academy of Engineering, a Sloan Foundation Fellow in Computer Science, and an ACM Fellow. She is recognized as an outstanding teacher and mentor, having received the Phi Beta Kappa teaching award in 1996, the Abrahmson Teaching Award in 1999, the Capers and Marion McDonald Award for Excellence in Mentoring and Advising in 2010, and the CRA-E Undergraduate Research Mentoring Award in 2017.

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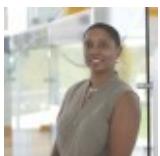
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and CSEE&T's Nancy Mead Award for Excellence in Software Engineering Education. She is an elected fellow of the ACM, the IEEE, and the AAAS.

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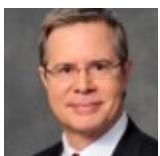


[Valerie Taylor](#)

[Argonne National Laboratory](#)

Valerie Taylor is the director of the Argonne National Laboratory Mathematics and Computer Science Division. She received her Ph.D. in electrical engineering and computer science from the University of California, Berkeley, in 1991. She then joined the faculty in the Electrical Engineering and Computer Science Department at Northwestern University, where she was a member of the faculty for 11 years. In 2003, she joined Texas A&M, where she served as head of the computer science and engineering department and senior associate dean of academic affairs in the College of Engineering and a Regents Professor and the Royce E. Wisenbaker Professor in the Department of Computer Science

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[Jeffrey S. Vitter](#)

[University of Mississippi](#)

Past Chancellor of the University of Mississippi and Distinguished Professor of Computer and Information Science. Previously Provost and Executive Vice Chancellor and Roy A. Roberts Distinguished Professor at the University of Kansas. Previously served in administrative leadership and faculty roles at Brown, Duke, Purdue, and Texas A&M. B.S. with highest honors in mathematics in 1977 from Notre Dame; Ph.D. in computer science in 1980 from Stanford; and M.B.A. in 2002 from Duke. Over 300 publications, primarily dealing with algorithmic aspects of big data. Fellow of the Guggenheim Society, AAAS, ACM, and IEEE.

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Determining the number of hidden layer and hidden neuron of neural network for wind speed prediction

Muhammad Ibnu Choldun Rachmatullah, Judhi Santoso and Kridanto Surendro

School of Electrical Engineering and Informatics, Institut Teknologi Bandung, Bandung, West Java, Indonesia

ABSTRACT

Artificial neural network (ANN) is one of the techniques in artificial intelligence, which has been widely applied in many fields for prediction purposes, including wind speed prediction. The aims of this research is to determine the topology of neural network that are used to predict wind speed. Topology determination means finding the hidden layers number and the hidden neurons number for corresponding hidden layer in the neural network. The difference between this research and previous research is that the objective function of this research is regression, while the objective function of previous research is classification. Determination of the topology of the neural network using principal component analysis (PCA) and K-means clustering. PCA is used to determine the hidden layers number, while clustering is used to determine the hidden neurons number for corresponding hidden layer. The selected topology is then used to predict wind speed. Then the performance of topology determination using PCA and clustering is then compared with several other methods. The results of the experiment show that the performance of the neural network topology determined using PCA and clustering has better performance than the other methods being compared. Performance is determined based on the RMSE value, the smaller the RMSE value, the better the neural network performance. In future research, it is necessary to apply a correlation or relationship between input attribute and output attribute and then analyzed, prior to conducting PCA and clustering analysis.

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Corresponding author
Muhammad Ibnu Choldun Rachmatullah, ibnucholdun@poltekpos.ac.id

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Additional Information and Declarations can be found on page 15

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Subjects Artificial Intelligence, Data Mining and Machine Learning

Keywords Neural network, Hidden layer, Hidden neuron, PCA, K-means clustering, Regression, Wind speed prediction

INTRODUCTION

The energy requirement continuously grows as the world population increases. Such energy requirement increases sometimes is not accompanied with the increase of supporting facilities and infrastructure development making several locations do not obtain sufficient electricity input. This case encourages the utilization of renewable energy in order to meet the world energy demand in various sectors including agriculture, education, health, road lighting, and community economy driving force (*Jamil & Zeeshan, 2019; Zhang et al., 2019*). Wind-based energy has long been utilized in irrigation sector, while other sources reveal that wind energy was firstly used in India (*Mathew, 2006*). Although it has long been

used in various sectors, wind speed prediction does not belong to an easy work due to its high strong randomness and volatility, whereas accurate wind speed prediction is needed in our life. One of the important factors in predicting wind speed is its accuracy ([Peiris, Jayasinghe & Rathnayake, 2021](#); [Yadav, Muneender & Santhosh, 2021](#)). As an example, the accuracy of wind speed prediction is essential in terms of wind power plant ([Zhang et al., 2019](#)).

Several different techniques have been used to predict the wind speed, including physical method ([Lange & Focken, 2009](#); [Li et al., 2013](#)), statistical method, and combination method between them. The use of physical method can be seen in the use of Computational Fluid Dynamics (CFD), where such approach does not depend on the historical data and can be used wider in all kinds of wind power plant including the newest wind power plant ([Li et al., 2013](#)). The use of statistical method is in the form of the use of auto regressive model (AR), moving average model (MA), autoregressive moving average model (ARMA), and auto regressive integrate moving average model (ARIMA) ([Lei et al., 2009](#)). In addition to these two methods, neural network is recently often used to predict the wind speed ([Jamil & Zeeshan, 2019](#); [Madhiarasan & Deepa, 2016](#); [Madhiarasan & Deepa, 2017](#); [Zhang et al., 2019](#)). The combination of the existing methods is also often used to predict the wind speed, such as the use of autoregressive fractionally integrated moving average and improved back-propagation neural network ([Wang & Li, 2019](#)).

Artificial neural networks, as a part of artificial intelligence methods have been widely used in many fields for prediction purposes ([Bakhshwain & Sagheer, 2021](#); [Rahman et al., 2021](#); [Zhao & Liu, 2021](#)), including wind speed prediction. One of the crucial factor for designing a neural network is its structure or topology, namely determining the hidden layers number and the hidden neurons number for corresponding hidden layer because it is closely related to the topological performance ([Aggarwal, 2018](#); [Koutsoukas et al., 2017](#); [Nitta, 2017](#)), but until now topology determination is still a complex and difficult problem ([Lee et al., 2018](#); [Naitzat, Zhitnikov & Lim, 2020](#); [Rahman et al., 2021](#)). Topology is one of the important hyperparameters in neural networks. Determining the topology that does not match the needs caused overfitting or underfitting in neural networks. Several researchers have conducted research to determine the neural network topology in various ways: methods based solely on the number of input and output attributes ([Sartori & Antsaklis, 1991](#); [Tamura & Tateishi, 1997](#)), trial and error ([Blanchard & Samanta, 2020](#); [Madhiarasan, 2020](#); [Madhiarasan & Deepa, 2016](#); [Madhiarasan & Deepa, 2017](#); [Sen & Özcan, 2021](#)) , and the rule of thumb ([Bakhshwain & Sagheer, 2021](#); [Carballal et al., 2021](#); [Rahman et al., 2021](#)).

In this research, the determination of the neural network topology use PCA and K-means clustering ([Rachmatullah, Santoso & Surendro, 2020](#)), but for the new objective function. Whereas in the previous research ([Ibnu Choldun, Santoso & Surendro, 2020](#); [Rachmatullah, Santoso & Surendro, 2020](#)) the determination of the neural network topology was used for the classification objective function, in this research it was used for the regression objective function, specifically to predict wind speed. The scientific major contribution of this research is the use of a new method to determine the neural network topology using PCA and clustering for the regression objective function. The main difference is that the attribute

classification objective function is categorical while the output regression objective function must be numeric. The performance measurement is also different, if the classification uses the accuracy rate, while if the regression uses error rate. The purpose of this research is to perform regression, so that the cumulative variance required is expected to be greater than classification, because the output domain for regression is continuous, while for classification is discrete. Then, topology performance of neural network in this research was compared with several other methods, namely: the Sartori method (*Sartori & Antsaklis, 1991*), the Tamura and Tateishi method (*Tamura & Tateishi, 1997*), the Madhiarasan and Deepa method(*Madhiarasan & Deepa, 2017*), the Madhiarasan method (*Madhiarasan, 2020*), and the Mahdi method (*Mahdi, Yousif & Melhum, 2021*).

The next section of this paper is structured as follows. The ‘Materials & Methods’ section contains the methodology of the proposed method starting from the data preparation to the topology evaluation. The ‘Results and Discussion’ section explains the results of the experiment and its discussion, especially about topology determination and topology evaluation. The ‘Conclusions and Future Work’ concludes and proposes future works containing a summary of the results of this study and provide direction for subsequent research studies.

MATERIALS & METHODS

The methods is presented with a clear outline as illustrated in Fig. 1. In general, the methods is divided into two main steps, namely the pre-training and the topology evaluation. The pre-training step was conducted before the model formation process of learning including preparation or selection of datasets, pre-processing data, and measurement of the topology of neural networks. Stages of topology evaluation were applied to manage the learning performance of neural networks based on the topology. The stage involves training, testing, and performance calculation. The proposed method focuses on determining the topology of neural networks for regression objective function which includes three main steps, namely:

1. Analyzing the dataset by applying PCA, therefore it can obtained significant principal components.
2. Performing clustering using the K-means technique for each corresponding principal component by changing the clusters number
3. Determining the optimal clusters number for each corresponding principal component by applying Elbow criteria, so that the optimal clusters number is obtained for each corresponding principal component.

Each stage will be explained in the next section.

Data preparation

This study aims to predict wind speed, so researchers choose a dataset providing attributes to predict wind speed. The dataset was meteorological data (London Meteorological data) downloaded from <http://www.urban-climate.net/content/data/9-data> for 2016 consisting of 8784 data. This dataset had many features, but researchers only selected attributes related to wind speed prediction. These attributes are input and output as in Table 1:

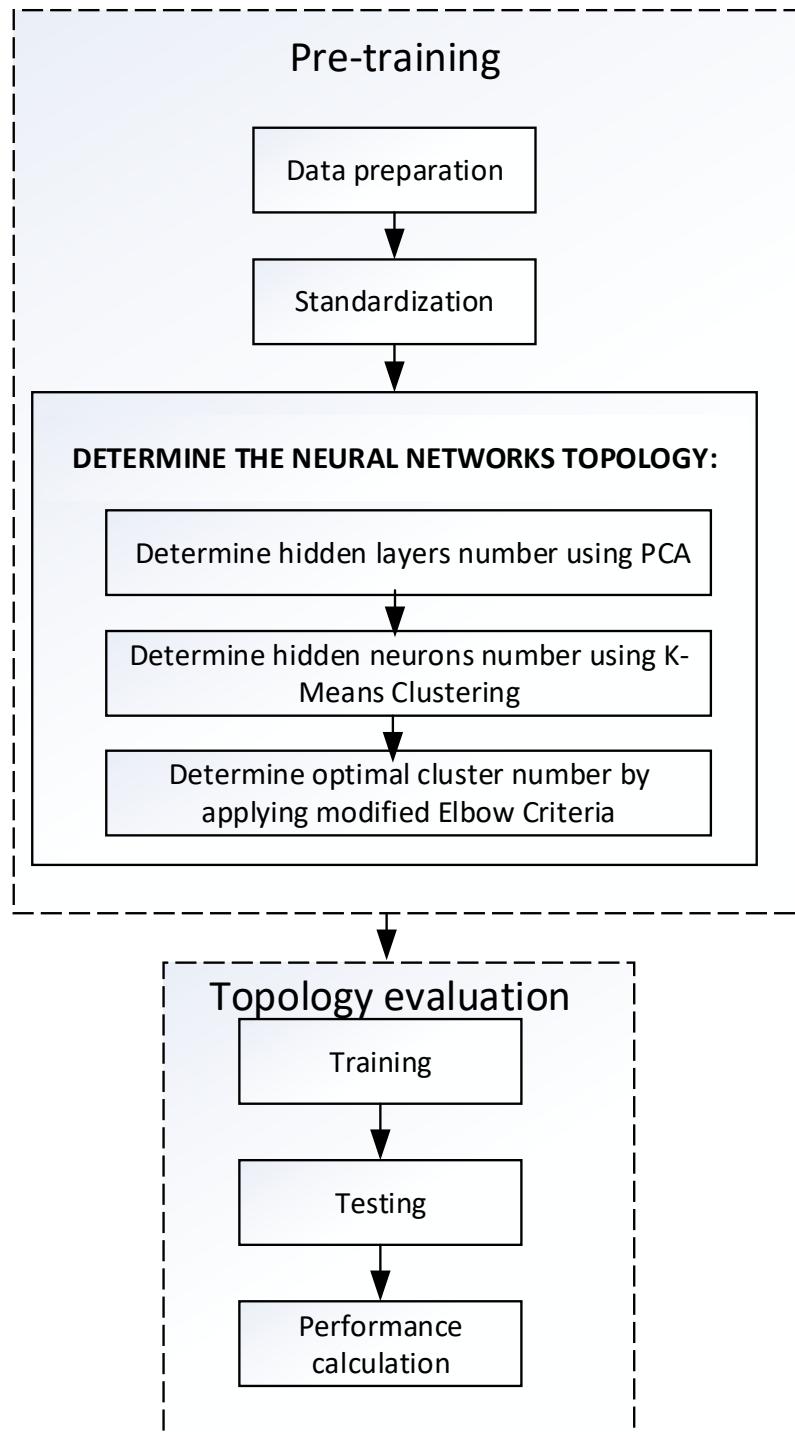


Figure 1 The methodology of proposed method.

Full-size DOI: 10.7717/peerjcs.724/fig-1

Table 1 Attribute used.

No.	Attribute name	Input/ Output	Range	Mean
1	CR10 temperature	Input	11.140–29.720	18.591
2	Last minute average temperature	Input	−1.267–32.400	12.413
3	Maximum hourly air temperature	Input	−1.172–33.480	12.809
4	Minimum hourly air temperature	Input	−1.280–31.540	12.063
5	Wind speed 10 minutes	Output	0.000–28.250	7.786

Table 2 Normalized attributes.

No.	Attribute name	Input/ Output	Range	Mean
1	CR10 temperature	Input	0.000–1.000	0.401
2	Last minute average temperature	Input	0.000–1.000	0.406
3	Maximum hourly air temperature	Input	0.000–1.000	0.403
4	Minimum hourly air temperature	Input	0.000–1.000	0.407
5	Wind speed 10 minutes	Output	0.000–1.000	0.276

Table 1 explains there are four input attributes, including CR10 Temperature, Last Minute Average Temperature, Maximum Hourly Air Temperature, and Minimum Hourly Air Temperature. These attributes have a role to predict the output attribute (Wind Speed). The range of values for these five attributes can be seen in column 4, while, the average can be seen in column 5.

Standardization

Standardization utilizes the normalization process so that data can be obtained with the consistent scale attributes. The normalization used is the Min-Max with a value between 0 and 1 using Eq. (1) (*Dharamvir, 2020*). The formula for normalization with Min-Max technique is as follows:

$$d' = \frac{d - \min_1}{\max_1 - \min_1} (\max_2 - \min_2) + \min_2 \quad (1)$$

d' = the new value of data, d = old data, \min_1 = the lowest value of corresponding attribute, \max_1 = the highest of corresponding attribute, $\min_2 = 0$, $\max_2 = 1$.

After reaching the normalization stage with min-max (0–1), **Table 2** shows that the five attributes now have the same range between 0 and 1 as shown in the fourth column and the average value shown in the fifth column.

Determining of neural network topology

In this research, the determination of the neural network topology to predict wind speed is based on previous research (*Ibnu Choldun, Santoso & Surendro, 2020; Rachmatullah, Santoso & Surendro, 2020*) that uses PCA and clustering with the K-means technique as illustrated in Fig. 2, but for the regression objective function.

In a neural network, increasingly complex features represent increasingly higher information content. Meanwhile, the high content of information in PCA is represented in

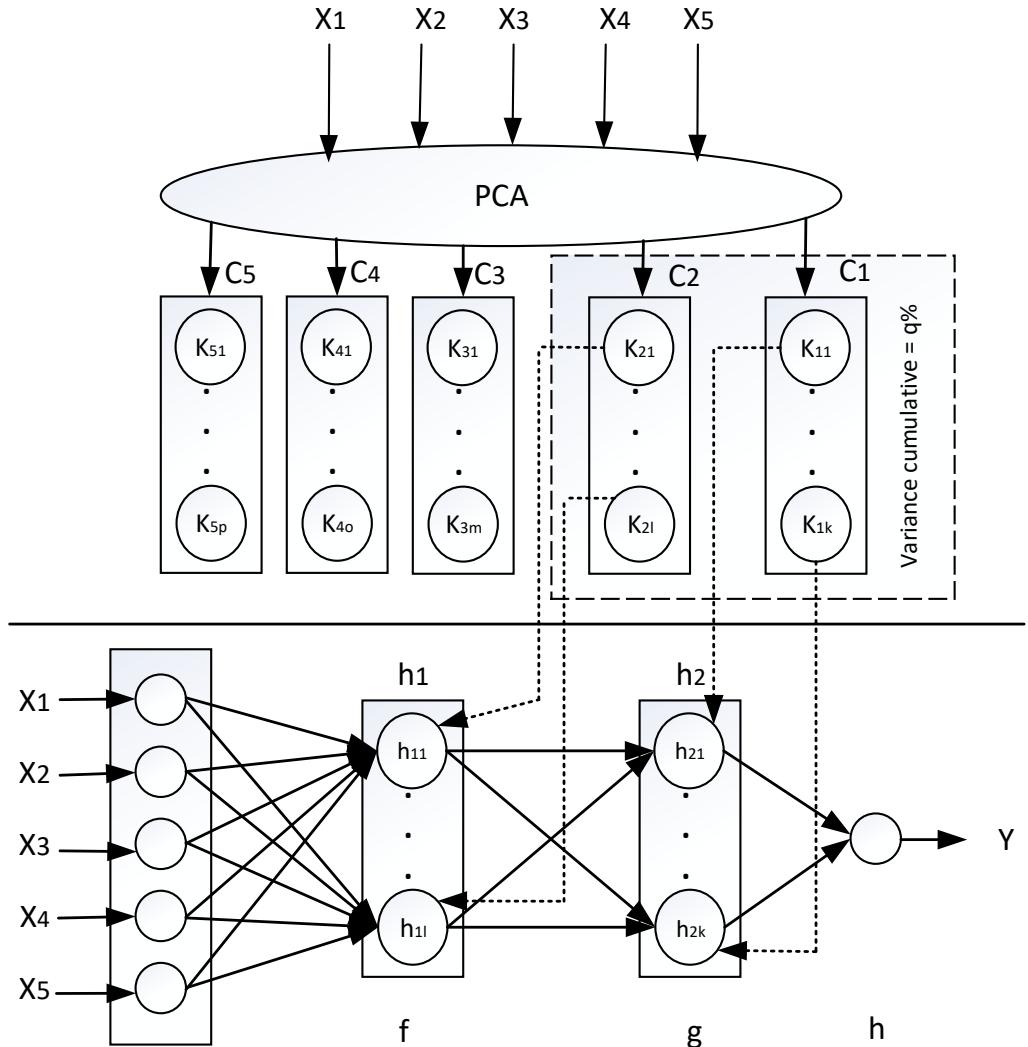


Figure 2 Determine neural networks topology for regression using PCA and clustering.

Full-size DOI: [10.7717/peerjcs.724/fig-2](https://doi.org/10.7717/peerjcs.724/fig-2)

the principal component which has a high variance. Therefore, the hidden layers that have more complex features are consistent with the PCA components that have higher variance. Accordance with this rationale, the hidden layer number in neural networks needed is consistent with the principal components number in PCA. Hence in this research, the determination of hidden layer number in neural networks based on principal components number obtained through PCA. This determination is accordance with the consideration that the PCA cumulative variance is compatible with the complexity of hidden layer in neural network as in Eq. (2).

$$\sum \text{Variance}(PC_i) \approx \sum \text{Complexity}(h_i) \quad (2)$$

PC_i is PCA component and h_i is the neural network hidden layer

So for example in the figure above, a dataset that has four attributes of input, after a principal component analysis is carried out, there will be four principal components where

the principal component equation is a input attributes linear combination ([Liu & Ding, 2020](#); [Ratner, 2017](#)). Since the input attributes number is four, the principal component equation is as follows:

$$\begin{aligned} PC_1 &= w_{11}x_1 + w_{12}x_2 + w_{13}x_3 + w_{14}x_4 + w_{15}x_5 \\ PC_2 &= w_{21}x_1 + w_{22}x_2 + w_{23}x_3 + w_{24}x_4 + w_{25}x_5 \\ PC_3 &= w_{31}x_1 + w_{32}x_2 + w_{33}x_3 + w_{34}x_4 + w_{35}x_5 \\ PC_4 &= w_{41}x_1 + w_{42}x_2 + w_{43}x_3 + w_{44}x_4 + w_{45}x_5 \end{aligned} \quad (3)$$

w = weight, x_i = ith input attribute

Of the four components, for example, only two principal components that have a cumulative variance q% were selected ([Yang, 2019](#)). The two principal components selected with the cumulative variance q% are the basis for determining the hidden layers number in neural network, namely using two hidden layers. Then we clustered each selected component using K-means clustering([Alguliyev, Alguliyev & Sukhostat, 2020](#); [Hancer, Xue & Zhang, 2020](#)). The optimal clusters number for corresponding principal component was determined using the Elbow criteria ([Shmueli et al., 2020](#)). The optimal clusters number for each component is the basis for determining the hidden neurons number in corresponding hidden layer on the neural network.

Topology evaluation

The training process was carried out with the amount of data as much as 70% of the dataset, while testing was carried out with 30% of the data from the dataset ([Nguyen et al., 2021](#)). Both the training and testing processes for each topology were repeated ten times by varying the initial weight values. For the regression objective function, the following performance measures can be used: Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), or Mean Square Error (MSE). MAPE and MAE are suitable for time series datasets. In this research, the dataset used is not time series data so that the performance measurement was selected using RMSE ([Namasudra, Dhamodharavadhani & Rathipriya, 2021](#)). Calculation of the topology performance of neural network is based on the value of the root mean of squared error (RMSE) with the formula:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^n (\hat{y}_i - y_i)^2} \quad (4)$$

where, N: the number of data, \hat{y}_i : the prediction value, y_i : the target value. Lower RMSE presents higher performance.

To compare the topology performance based on PCA and clustering, it is necessary to compare with several other methods. Some of these methods are:

1. Sartori method ([Sartori & Antsaklis, 1991](#)) used one hidden layer with

The neuron number = $N - 1$

N = the input feature number.

(5)

Table 3 PCA and clustering of the wind dataset.

Component	Variance	Cumulative	Clustering
PC 1	0.943	0.943	10
PC 2	0.056	0.999	3
PC 3	0.001	1.000	2
PC 4	0.000	1.000	2

2. Tamura and Tateishi method (*Tamura & Tateishi, 1997*) used two hidden layers, where

The neuron number of the corresponding hidden layer : $N/2 + 3$

N = the number of input feature. (6)

3. Madhiarasan and Deepa method (*Madhiarasan & Deepa, 2017*) used one hidden layer and through trial and error, it was found that the number of neurons was 14.

4. Madhiarasan method (*Madhiarasan, 2020*), used one hidden layer and through trial and error, it was found that the number of neurons was 44.

5. Mahdi et al. method (*Mahdi, Yousif & Melhum, 2021*) used one hidden layer and through trial and error, it was found that the number of neurons was 20.

To calculate the performance of the topology we use the Windows 10 operating system and Rapidminer 9.5 tools.

RESULTS AND DISCUSSION

In this section, the process of determining the neural network topology will be presented as a result of the application of principal component analysis(PCA), clustering with K-means method and the application of modified Elbow criteria to the wind dataset.

Determine the topology of neural networks using PCA and K-means clustering

After normalization, both input attributes and output attributes have a value range between 0 and 1 as presented in Standardization section. Principal component analysis was done on the four normalized input attributes.. The PCA results can be seen in the second and third columns of **Table 3**. The first PCA principal component has a highest variance which is of 0.943 (94.3%) so that the cumulative variance is also 0.943. The second principal component of PCA has a second highest variance which is 0.056 (5.6%) so the cumulative variance is $0.943 + 0.056 = 0.999$. The variance for each main component was obtained from the proportion between the eigenvalues of a component and the total eigenvalues of all components. Likewise for the third component and fourth component can be seen in the second and third columns of **Table 3**.

For each component that has been generated from the PCA process, clustering is carried out so that the optimal clusters number of clusters is obtained. The clustering application is carried out using the K-means method, while to determine the optimal cluster number using the modified Elbow criteria. The optimal clusters number has been obtained based

Table 4 The result of application of K-means clustering and modified elbow criteria for the first component.

N	wss	N	wss	N	wss	N	wss
2	0.035	15	0.001	27	0.000	39	0.000
3	0.019	16	0.001	28	0.000	40	0.000
4	0.012	17	0.001	29	0.000	41	0.000
5	0.008	18	0.001	30	0.000	42	0.000
6	0.006	19	0.001	31	0.000	43	0.000
7	0.004	20	0.001	32	0.000	44	0.000
8	0.003	21	0.001	33	0.000	45	0.000
9	0.003	22	0.000	34	0.000	46	0.000
10	0.002	23	0.000	35	0.000	47	0.000
11	0.002	24	0.000	36	0.000	48	0.000
12	0.002	25	0.000	37	0.000	49	0.000
13	0.001	26	0.000	38	0.000	50	0.000
14	0.001						

on the wss value, that is, when the wss value in a row (at least three in a row) has remained relatively unchanged (*Rachmatullah, Santoso & Surendro, 2020*). The examples of applying the modified Elbow criteria are shown in **Table 4**, which is the result of applying these criteria to the first PCA principal component that has the highest variance. Hence, the number of clusters gradually increased from 2 to 50, while the wss value calculation results appeared. At $N = 10, 11$, and 12 the value of the three wss values in a row does not change, so it can be concluded that the number of neurons for the first component is 10.

The results of K-means clustering and applying the modified Elbow criteria for corresponding component can be seen in the fourth column of **Table 3**. For example, for the PCA first component the optimal clustersnumber is 10, for the PCA second component the optimal clusters number is 3, and so on with the same explanation.

The results obtained from the PCA process and K-means clustering were used in determining the neural network topology. The determination of this topology consists of determining the hidden layers number and the neurons number in corresponding of these hidden layers. Since it had reached the cumulative variance of 90% using one component, the topology of the neural network was evaluated using one hidden layer to four hidden layers. As an explanation, if one component is to be used which has the optimal number of clusters is 10, then the topology is to use one hidden layer with the neurons number is 10; if two components are to be used, then the hidden layers number is two in which the first hidden layer has 3 neurons and meanwhile the second hidden layer has 10 neurons; and so on in the same explanation as shown in **Fig. 3**. This figure shows the topology that use four hidden layers. The first principal component of PCA, which has the highest variance, corresponds to the hidden layer closest to the output layer.

Performance comparison

The performance comparison of the topology of neural network from the results of PCA and clustering, it needs analysis of each of the topologies and a comparison with five

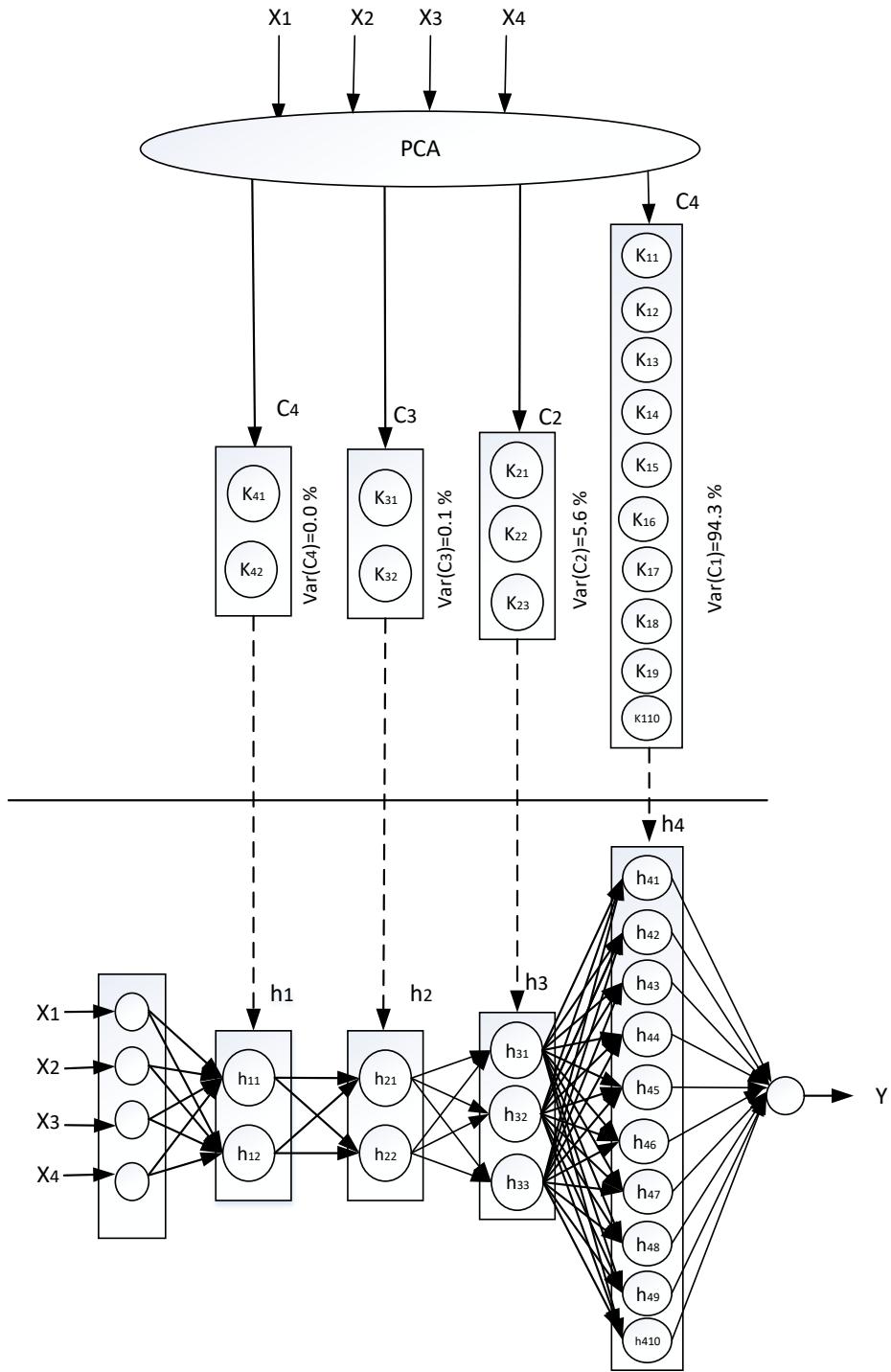


Figure 3 Mapping PCA to neural network. (X_1 = CR10 temperature, X_2 = Last minute average temperature, X_3 = Maximum hourly air temperature, X_4 = Minimum Hourly air temperature, Y = Wind speed 10 minutes).

Full-size DOI: [10.7717/peerjcs.724/fig-3](https://doi.org/10.7717/peerjcs.724/fig-3)

Table 5 The RMSE value of topology with cycles is 100.

No.	Seed	Topology			
		10	3,10	2,3,10	2,2,3,10
1	0	0.1284	0.1266	0.1299	0.1534
2	1	0.1197	0.12	0.1199	0.1424
3	2	0.1522	0.1519	0.1524	0.1938
4	3	0.1484	0.1546	0.1562	0.1626
5	4	0.1206	0.1212	0.1220	0.1430
6	5	0.1607	0.1533	0.1541	0.1748
7	10	0.1288	0.1266	0.1274	0.1494
8	15	0.1198	0.1196	0.1196	0.1387
9	20	0.1311	0.1292	0.1301	0.1433
10	25	0.1294	0.131	0.1255	0.1384
Mean		0.13391	0.1334	0.13371	0.15398

methods proposed by other researchers. The Sartori method and the Tamura and Tateishi method with $N = 4$ (input attribute number) respectively get topology (3) and topology (5,5). Three other methods are the Madhiarasan and Deepa methods, the Madhiarasan method, and the Mahdi method which uses one hidden layer sequentially using topology (14), topology (44), and topology (20). These five method proposed by the other researchers is used as a comparison with the the method used by researchers.

Table 5 presents the RMSE mean of each topology determined by PCA process and K-means clustering, where each topology is applied to the process of learning using a neural network with 100 cycles. For each topology, each experiment was repeated ten times by varying the seed. The column “Topology” presents the hidden layers number and the neurons number for each topology. As an explanation, column “3,10” shows a topology consisting of two hidden layers with the first hidden layer has 3 neurons and the second hidden layer has 10 neurons. The values in the table shows the RMSE value, while the bottom row present the mean of RMSE from 10 repetitions.

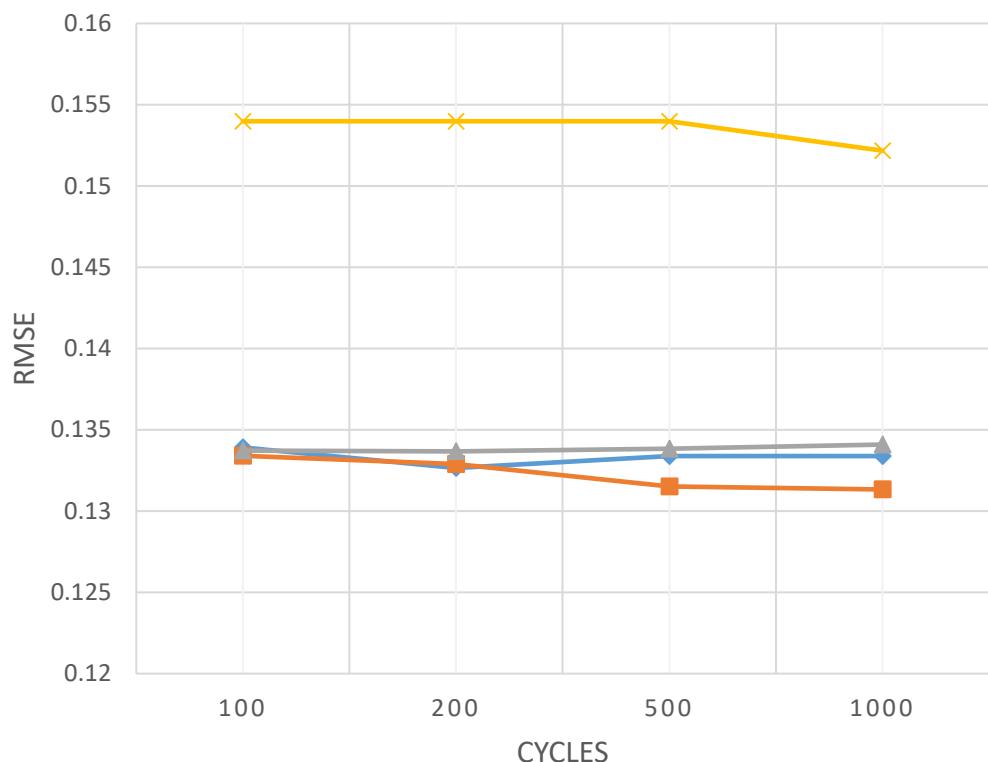
In the same way, the experiments in **Table 5** also implement some different cycles, including 200 cycle, 500 cycle, and 1,000 cycle. The summary that shows the mean value of each cycles is displayed in **Table 6**, while in graphical form is manifested in **Fig. 4**. The values in **Table 6** explains the average RMSE value of 10 repetitions for each topology, the details of which can be worked out following **Table 5**. Through the same experiment, **Table 6** were also carried out for the number of cycles of 200 cycle, 500 cycle, and 1,000 cycle.

In **Fig. 4**, the horizontal axis is the cycles number, and the vertical axis is the mean value of RMSE. The graph presents the mean of RMSE values for each topology in each cycle. The graph in **Fig. 4** shows the topology (3,10) has a tendency of RMSE mean values lower than other topologies, then followed by topology (10), topology (2,3,10) and topology (2,2,3,10). The graph also presents the addition of the hidden layers number does not provide a guarantee to reduce the RMSE value. Based on the topology from PCA and clustering, it has two hidden layers, which gives the lowest RMSE value, so it proves the

Table 6 RMSE mean of topology (PCA and K-means clustering).

Cycles	Topology			
	10	3,10	2,3,10	2,2,3,10
100	0.13391	0.1334	0.13371	0.15398
200	0.13265	0.1329	0.13367	0.15398
500	0.13339	0.13151	0.13384	0.15398
1000	0.13338	0.13133	0.13409	0.15217

— ◆ — 10 — ■ — 3,10 — ▲ — 2,3,10 — ✕ — 2,2,3,10

**Figure 4** RMSE value for topology determined using PCA and clustering.

Full-size DOI: [10.7717/peerjcs.724/fig-4](https://doi.org/10.7717/peerjcs.724/fig-4)

best performance of the topology. Mapping from PCA and clustering into the topology of neural network gives the best performance, namely topology (3,10) as shown in Fig. 5. This topology that uses two hidden layers requires a cumulative variance of 99%, so that the selected topology will be compared with the topology of other researchers. This also proves that the cumulative variance PCA required for the regression objective function is greater than the classification objective function as has been done in previous research: for multi-class classification it needs a PCA cumulative variance of about 70% ([Ibnu Choldun, Santoso & Surendro, 2020](#); [Rachmatullah, Santoso & Surendro, 2020](#)) while for binary classification it needs a PCA cumulative variance of about 40% ([Rachmatullah, Santoso & Surendro, 2020](#)).

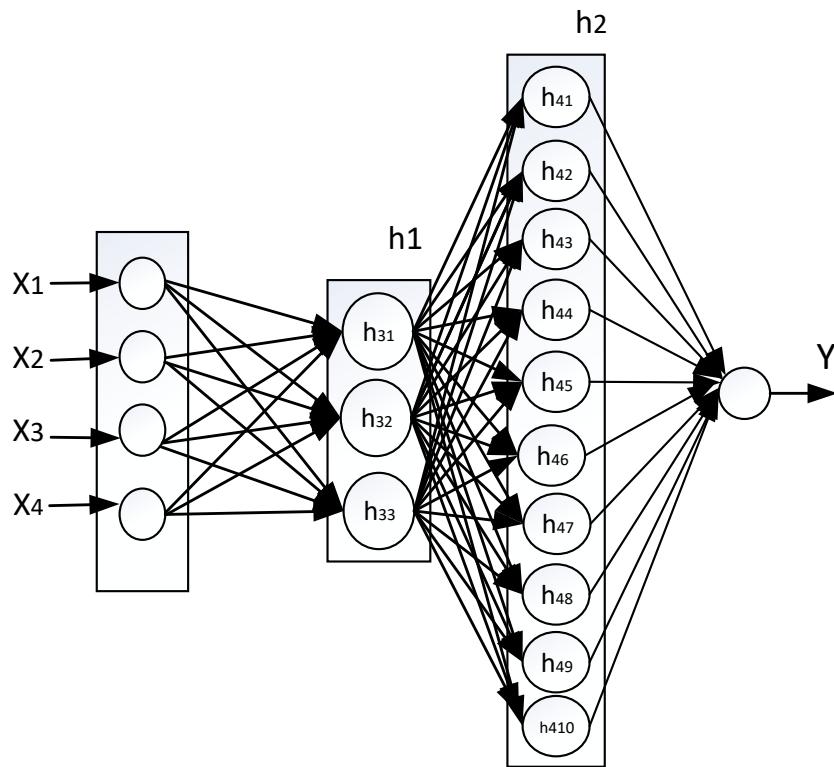


Figure 5 The original topology which has the best performance. (X_1 = CR10 temperature, X_2 = Last minute average temperature, X_3 = Maximum hourly air temperature, X_4 = Minimum hourly air temperature, Y = Wind speed 10 minutes).

Full-size DOI: 10.7717/peerjcs.724/fig-5

In this research we also processes the dataset as listed in [Table 1](#) using the topologies that are compared so that each topology has an RMSE value. [Table 7](#) shows the experiment results on the dataset using the method used by researchers and five other methods used by other researchers. This table presents the comparison of the RMSE between all topologies. Each topology is applied to the learning process using a neural network with 100 cycles.

The presentation of [Table 7](#) is the same as the presentation of [Table 5](#) as previously explained and also implemented in some different cycles, including 200 cycle, 500 cycle, and 1,000. The summary that shows the mean the mean values of each cycle is as shown in [Table 8](#), whereas the graph can be seen in [Fig. 6](#). The horizontal axis, vertical axis, and graphs for [Fig. 6](#) are explained in the same way as [Fig. 4](#). [Figure 6](#) exposes the RMSE value for comparison between the topology used by researcher (PCA and Clustering method) and the five topologies that used by other researchers, namely: the Sartori method, the Tamura and Tateishi method, the Madhiarasan and Deepa method, the Madhiarasan method, and Mahdi method.

In [Fig. 6](#), the horizontal axis is the cycles number, and the vertical axis is the mean value of RMSE. The graph presents the mean of RMSE values for each topology in each cycle. The graph in [Fig. 6](#) shows the topology used by researchers has a tendency of RMSE mean values lower than other topologies, then followed by Tamura and Tateishi topology

Table 7 The comparison of topology RMSE value with cycles is 100.

No.	Seed	Topology					
		Researcher (3,10)	Sartori (3)	Tateishi& Tamura (5,5)	Madhiarasan& Deepa (14)	Madhiarasan (44)	Mahdi (20)
1	0	0.1266	0.1378	0.1264	0.1287	0.1283	0.1287
2	1	0.1200	0.1262	0.1202	0.1198	0.1194	0.1198
3	2	0.1519	0.1500	0.1525	0.1512	0.1508	0.1515
4	3	0.1546	0.1475	0.1545	0.1485	0.1531	0.1485
5	4	0.1212	0.1312	0.1218	0.1208	0.1196	0.1196
6	5	0.1533	0.1533	0.1520	0.1618	0.1597	0.1608
7	10	0.1266	0.1418	0.1266	0.1287	0.1285	0.1291
8	15	0.1196	0.1309	0.1196	0.1197	0.1196	0.1200
9	20	0.1292	0.1415	0.1289	0.1306	0.1294	0.1309
10	25	0.1310	0.1286	0.1314	0.1282	0.1193	0.1296
Mean		0.1334	0.13888	0.13339	0.1338	0.13277	0.13385

Table 8 RMSE mean of topology (PCA + clustering) and other topology.

Cycles	Topology					
	Researcher (3,10)	Sartori (3)	Tamura& Tateishi (5,5)	Madhiarasan& Deepa (14)	Madhiarasan (44)	Mahdi (20)
100	0.13340	0.13888	0.13339	0.13380	0.13277	0.13385
200	0.13290	0.13809	0.13174	0.13253	0.13285	0.13329
500	0.13151	0.13666	0.13228	0.13257	0.13298	0.13374
1000	0.13133	0.13599	0.13171	0.13311	0.13214	0.13381

(5,5), Madhiarasan (44), Madhiarasan and Deepa topology (14), Mahdi topology (20), and Sartori topology (3). The graph also shows that the using two hidden layers tends to have a lower RMSE than using only one hidden layer. The topology used by researchers based on PCA and clustering with two hidden layers, which gives the lowest RMSE value, so this proves that this topology has the best performance compared to the topologies used by other researchers.

Patterson and Gibson proposed to provide hidden neurons in large numbers in the network so that the performance of neural networks is better. But network performance can be degraded when the number of neurons is too large because it may have several false connections ([Patterson & Gibson, 2017](#)). For example, using a higher number of neurons in Madhiarasan (44) than in Madhiarasan and Deepa topology (14), Mahdi topology (20), and Sartori topology (3), can improve the neural networks performance. However, increasing the number of neurons using only one hidden layer does not always guarantee an increase in performance, such as the performance of Madhiarasan (44) which is lower than the topology that uses two hidden layers with fewer neurons, the Tamura & Tateishi (5,5) topology and the proposed topology (3,10). This study also shows that the cumulative variance for the regression objective function, in this study 99% greater than the cumulative variance for the classification objective function in previous studies

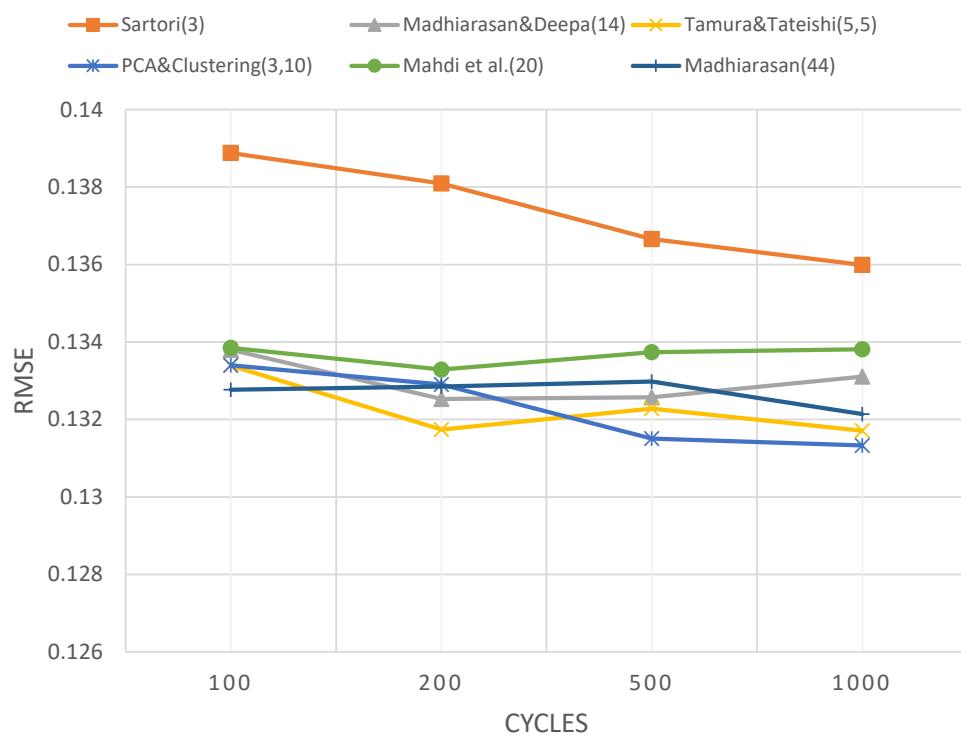


Figure 6 The comparison of the RMSE value between topology used by researchers and other topologies.

Full-size DOI: [10.7717/peerjcs.724/fig-6](https://doi.org/10.7717/peerjcs.724/fig-6)

(*Rachmatullah, Santoso & Surendro, 2020*), where for binary classification needs a PCA cumulative variance of 38.9%, while the multi-class classification needs a PCA cumulative variance of 69.7%.

CONCLUSIONS AND FUTURE WORK

In this research paper, performance analysis of various neural network is compared to predict the wind speed. Comparison was made between the PCA and clustering method and several other methods. The PCA and clustering method uses PCA to set the hidden layers number, whereas K-means clustering of these components formed from PCA is used to determine the optimal clusters number used as a guidance to set the neurons number in corresponding hidden layer. The experimental results report that the topology originating from PCA and clustering has a fairly good performance compared to other methods by looking at the mean value of RMSE. The topology of Neural network determination using PCA and clustering can provide optimal performance.

In future research, it is necessary to apply a correlation or relationship between input attributes and output attributes and then analyzed, prior to conducting PCA and clustering analysis. Variations in input attributes also need to be analyzed before implementing PCA and K-means clustering. Considering correlation of attributes and the variation of attributes is expected to produce a topology of neural network design that has better

performance. Future researches can also use other clustering methods to determine the number of neurons.

ADDITIONAL INFORMATION AND DECLARATIONS

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The authors declare there are no competing interests.

Author Contributions

- Muhammad Ibnu Choldun Rachmatullah, Judhi Santoso and Kridanto Surendro conceived and designed the experiments, performed the experiments, analyzed the data, performed the computation work, prepared figures and/or tables, authored or reviewed drafts of the paper, and approved the final draft.

Data Availability

The following information was supplied regarding data availability:

The London Meteorological data for 2016 is available from: <http://www.urban-climate.net/content/data/9-data>.

Supplemental Information

Supplemental information for this article can be found online at <http://dx.doi.org/10.7717/peerj-cs.724#supplemental-information>.

REFERENCES

- Aggarwal CC. 2018. *Neural networks and deep learning*. New York: Springer International Publishing.
- Alguliyev RM, Aliguliyev RM, Sukhostat LV. 2020. Efficient algorithm for big data clustering on single machine. *CAAI Transactions on Intelligence Technology* 5(1):9–14 DOI [10.1049/trit.2019.0048](https://doi.org/10.1049/trit.2019.0048).
- Bakhshwain N, Sagheer A. 2021. Online tuning of hyperparameters in deep LSTM for time series applications. *International Journal of Intelligent Engineering and Systems* 14(1):212–220 DOI [10.22266/IJIES2021.0228.21](https://doi.org/10.22266/IJIES2021.0228.21).
- Blanchard T, Samanta B. 2020. Wind speed forecasting using neural networks. *Wind Engineering* 44(1):33–48 DOI [10.1177/0309524X19849846](https://doi.org/10.1177/0309524X19849846).
- Carballal A, Cedron F, Santos I, Santos A, Romero J. 2021. Minimal neural network topology optimization for aesthetic classification. *Neural Computing and Applications* 33(1):107–119 DOI [10.1007/s00521-020-05550-x](https://doi.org/10.1007/s00521-020-05550-x).

- Dharamvir AKV.** 2020. Data normalization techniques on intrusion detection for dataset applications. *International Journal of Advanced Science and Technology* **29**(7s):5083–5093.
- Hancer E, Xue B, Zhang M.** 2020. A survey on feature selection approaches for clustering. *Artificial Intelligence Review* **53**(6):4519–4545 DOI [10.1007/s10462-019-09800-w](https://doi.org/10.1007/s10462-019-09800-w).
- Ibnu Choldun RM, Santoso J, Surendro K.** 2020. Determining the number of hidden layers in neural network by using principal component analysis. *Advances in Intelligent Systems and Computing* **1038**:490–500 DOI [10.1007/978-3-030-29513-4_36](https://doi.org/10.1007/978-3-030-29513-4_36).
- Jamil M, Zeeshan M.** 2019. A comparative analysis of ANN and chaotic approach-based wind speed prediction in India. *Neural Computing and Applications* **31**(10):6807–6819 DOI [10.1007/s00521-018-3513-2](https://doi.org/10.1007/s00521-018-3513-2).
- Koutsoukas A, Monaghan KJ, Li X, Huan J.** 2017. Deep-learning: investigating deep neural networks hyper-parameters and comparison of performance to shallow methods for modeling bioactivity data. *Journal of Cheminformatics* **9**(1):1–13 DOI [10.1186/s13321-017-0226-y](https://doi.org/10.1186/s13321-017-0226-y).
- Lange M, Focken U.** 2009. *Physical Approach to Short-Term Wind Power Prediction*. New York: Springer-Verlag.
- Lee S, Ha J, Zokhirova M, Moon H, Lee J.** 2018. Background information of deep learning for structural engineering. *Archives of Computational Methods in Engineering* **25**(1):121–129 DOI [10.1007/s11831-017-9237-0](https://doi.org/10.1007/s11831-017-9237-0).
- Lei M, Shiyan L, Chuanwen J, Hongling L, Yan Z.** 2009. A review on the forecasting of wind speed and generated power. *Renewable and Sustainable Energy Reviews* **13**(4):915–920 DOI [10.1016/j.rser.2008.02.002](https://doi.org/10.1016/j.rser.2008.02.002).
- Li L, Liu YQ, Yang YP, Han S, Wang YM.** 2013. A physical approach of the short-term wind power prediction based on CFD pre-calculated flow fields. *Journal of Hydrodynamics* **25**(1):56–61 DOI [10.1016/S1001-6058\(13\)60338-8](https://doi.org/10.1016/S1001-6058(13)60338-8).
- Liu C, Ding Q.** 2020. A modified algorithm for the logistic sequence based on PCA. *IEEE Access* **8**:45254–45262 DOI [10.1109/ACCESS.2020.2978503](https://doi.org/10.1109/ACCESS.2020.2978503).
- Madhiarasan M.** 2020. Accurate prediction of different forecast horizons wind speed using a recursive radial basis function neural network. *Protection and Control of Modern Power Systems* **5**(1):1–9 DOI [10.1186/s41601-020-00166-8](https://doi.org/10.1186/s41601-020-00166-8).
- Madhiarasan M, Deepa SN.** 2016. A novel criterion to select hidden neuron numbers in improved back propagation networks for wind speed forecasting. *Applied Intelligence* **44**(4):878–893 DOI [10.1007/s10489-015-0737-z](https://doi.org/10.1007/s10489-015-0737-z).
- Madhiarasan M, Deepa SN.** 2017. Comparative analysis on hidden neurons estimation in multi layer perceptron neural networks for wind speed forecasting. *Artificial Intelligence Review* **48**(4):449–471 DOI [10.1007/s10462-016-9506-6](https://doi.org/10.1007/s10462-016-9506-6).

- Mahdi BH, Yousif KM, Melhum AI.** 2021. Application of artificial neural network to predict wind speed: case study in Duhok City. *Iraq. Journal of Physics: Conference Series* **1829**(1):1–7 DOI [10.1088/1742-6596/1829/1/012002](https://doi.org/10.1088/1742-6596/1829/1/012002).
- Mathew S.** 2006. *Wind energy: fundamentals, resource analysis, and economics*. 1. Heidelberg: Springer-Verlag.
- Naitzat G, Zhitnikov A, Lim LH.** 2020. Topology of deep neural networks. *ArXiv* 21:1–40.
- Namasudra S, Dhamodharavadhani S, Rathipriya R.** 2021. Nonlinear neural network based forecasting model for predicting COVID-19 cases. *Neural Processing Letters* DOI [10.1007/s11063-021-10495-w](https://doi.org/10.1007/s11063-021-10495-w).
- Nguyen QH, Ly H-B, Ho LS, Al-Ansari N, Le HV, Tran VQ, Prakash I, Pham BT.** 2021. Influence of data splitting on performance of machine learning models in prediction of shear strength of soil. *Mathematical Problems in Engineering* **2021**:4832864 DOI [10.1155/2021/4832864](https://doi.org/10.1155/2021/4832864).
- Nitta T.** 2017. Resolution of singularities introduced by hierarchical structure in deep neural networks. *IEEE Transactions on Neural Networks and Learning Systems* **28**(10):2282–2293 DOI [10.1109/TNNLS.2016.2580741](https://doi.org/10.1109/TNNLS.2016.2580741).
- Patterson J, Gibson A.** 2017. *Deep learning: a practitioner's approach*. Boston: O'Reilly.
- Peiris AT, Jayasinghe J, Rathnayake U.** 2021. Forecasting wind power generation using artificial neural network: Pawan Danawi —a Case Study from Sri Lanka. *Journal of Electrical and Computer Engineering* **2021**:5577547 DOI [10.1155/2021/5577547](https://doi.org/10.1155/2021/5577547).
- Rachmatullah MIC, Santoso J, Surendro K.** 2020. A novel approach in determining neural networks architecture to classify data with large number of attributes. *IEEE Access* **8**:204728–204743 DOI [10.1109/access.2020.3036853](https://doi.org/10.1109/access.2020.3036853).
- Rahman MA, Muniyandi R, Albashish D, Rahman MM, Usman OL.** 2021. Artificial neural network with Taguchi method for robust classification model to improve classification accuracy of breast cancer. *PeerJ Computer Science* **7**:2–27 DOI [10.7717/PEERJ-CS.344](https://doi.org/10.7717/PEERJ-CS.344).
- Ratner B.** 2017. *Statistical and machine-learning data mining: techniques for better predictive modeling and analysis of big data*. New York: CRC Press.
- Sartori MA, Antsaklis PJ.** 1991. A simple method to derive bounds on the size and to train multilayer neural networks. *IEEE Transactions on Neural Networks* **2**(4):467–471 DOI [10.1109/72.88168](https://doi.org/10.1109/72.88168).
- Sen M, Özcan M.** 2021. Maximum wind speed forecasting using historical data and artificial neural networks modeling. *International Journal of Energy Applications and Technologies* **8**(1):6–11 DOI [10.31593/ijeat.800937](https://doi.org/10.31593/ijeat.800937).
- Shmueli G, Bruce PC, Yahav I, Patel NR.** 2020. *Data mining for business analytics: concepts, techniques, and applications*. New Jersey: John Wiley & Sons.

- Tamura S, Tateishi M. 1997.** Capabilities of a four-layered feedforward neural network: four layers versus three. *IEEE Transactions on Neural Networks* **8**(2):251–255 DOI [10.1109/72.557662](https://doi.org/10.1109/72.557662).
- Wang J, Li Y. 2019.** An innovative hybrid approach for multi-step ahead wind speed prediction. *Applied Soft Computing Journal* **78**:296–309 DOI [10.1016/j.asoc.2019.02.034](https://doi.org/10.1016/j.asoc.2019.02.034).
- Yadav GR, Muneender E, Santhosh M. 2021.** Wind speed prediction using hybrid long short-term memory neural network based approach. In: *International conference on sustainable energy and future electric transportation (SeFeT)*. DOI [10.1109/sefet48154.2021.9375644](https://doi.org/10.1109/sefet48154.2021.9375644).
- Yang X-S. 2019.** *Introduction to algorithms for data mining and machine learning*. London: Academic Press.
- Zhang Y, Yang S, Guo Z, Guo Y, Zhao J. 2019.** Wind speed forecasting based on wavelet decomposition and wavelet neural networks optimized by the Cuckoo search algorithm. *Atmospheric and Oceanic Science Letters* **12**(2):107–115 DOI [10.1080/16742834.2019.1569455](https://doi.org/10.1080/16742834.2019.1569455).
- Zhao H, Liu S. 2021.** Tracing mechanism of sports competition pressure based on back-propagation neural network. *Complexity* **2021**:6652896 DOI [10.1155/2021/6652896](https://doi.org/10.1155/2021/6652896).