Predicting tree failure likelihood for utility risk mitigation via a novel convolutional neural network

1   Introduction

Utilities have been concerned with tree-related outages for many years, but much of the work to quantify them has been done in-house: Utilities contract with a consultant who analyzes tree-related outages (or interruptions). In general, tree-related outages are due to contact between tree parts and lines. Sometimes, the contact is due to growth of branches into the lines; sometimes it is due to branch failure; sometimes it is due to tree failure (either uprooting or trunk failure). When outages occur, the economic costs can be substantial. From 2005 to 2015, [1] computed the annual economic cost of outages in the state of Connecticut; the mean was approximately $8.3 bn. Outages due to contact from branch growth or branch failure can be mitigated by line clearance tree trimming. Estimates vary, but the annual amount that utilities spend on tree trimming operations is typically in the billions of dollars [2]. Despite the comparatively high annual cost of tree trimming, studies have repeatedly shown that trimming branches away from the wires reduces the number of outages (sometimes classified as "preventable" outages). For example, in Massachusetts, Simpson and Van Bossuyt [3] reported that tree failure caused 40% of preventable tree-caused outages, but removing or severely pruning high risk trees improved reliability by 20% to 30%. In a more recent (and sophisticated) analysis in Connecticut, Parent et al. [4] showed that enhanced tree trimming reduced outages during storms. And using a statistical model to predict outages based on data from two Gulf Coast states in the USA, Nateghi et al. [5] demonstrated that prediction models were less uncertain when they included the effect of tree trimming; models including wind speed without considering the effect of trimming were not as accurate.

Trimming can be effective because both structurally-deficient and structurally-sound branches adjacent to or overhanging the lines in proximity are removed, reducing the likelihood of contact. However, it cannot eliminate tree-related outages. Failure of trees away from the right-of-way can still impact the lines and cause outages [2]. The proportion of tree failures away from the wires that cause outages varies and has not been rigorously quantified. Guggenmoos [6] estimated that 95% of tree-caused outages in the Pacific Northwest region of the USA, were due to tree failure, and Wismer [7] reported approximately 25% of interruptions in Illinois, USA were caused by trees that uprooted or broke in the stem. Predicting the likelihood of failure is an inexact science, but tree risk assessment best management practices have been developed [8, 9]. Assessing risk includes assessing the likelihood of failure, the likelihood of impact, and the severity of consequences. Likelihood of failure depends on the anticipated loads on the tree and its load-bearing capacity. The likelihood of impact depends on proximity to the target (the lines, poles, and other hardware—"infrastructure"—in the case of utility tree risk assessment), the target's occupancy rate (which is constant for utility lines) and whether the target is sheltered, for example by neighboring trees. Severity of consequences depends on the damage done to the infrastructure and, more importantly in some cases, the economic costs and disruption associated with outages—this, in turn,

is partially related to the size of the tree or tree part that fails, and how much momentum it has when it impacts the infrastructure.

Assessing risk of individual trees can be costly because of the time required to complete the assessment. In some situations, a less time-consuming assessment may be justified to reduce costs—a "Level 1" assessment (Smiley et al. 2017). Studies have shown that trees with greater risk ratings were more likely to be detected from Level 1 risk assessments conducted in a moving vehicle in Rhode Island, USA [10] and Florida, USA [11] . The utility of Level 1 assessments in Rhode Island and Florida suggests that artificial intelligence (AI) tools may be an effective way to reduce the cost of tree risk assessment.

AI-based image analysis is relatively widely used, even in engineering applications such as earthquake risk assessment [12, 13] and structural health monitoring [14]. A relevant application for tree species identification using a convolutional neural network (CNN) was even recently demonstrated [15]. Yet, AI has not been applied to the problem of tree-utility line risk assessment—one that is complicated by the very large number of tree species to be considered, seasonal variation in tree appearance and associated risk and local meteorological conditions. However, the flexibility and power of CNNs, appears promising. In this paper, we demons In the remainder of this paper, we first provide a background on CNN which is critical for sustainability in critical infrastructural systems. Our goal is to further demonstrate an innovative automated approach to tree risk assessment using an AI tool that can be readily deployed for use in various locations and also continually improved through subsequent training on new datasets.

2 Background

3 Data

4 Methods

5 Results and Discussion

6 Conclusion

References

[1]   Marcello Graziano, Peter Gunther, Adam Gallaher, Fred V. Carstensen, and Brian Becker. "The Wider Regional Benefits of Power Grids Improved Resilience through Tree-Trimming Operations Evidences from Connecticut, USA". In: *Energy Policy* 138 (Mar. 1, 2020), p. 111293.

[2]   Siegfried Guggenmoos. "EFFECTS OF TREE MORTALITY ON POWER LINE SECURITY". In: *Journal of Arboriculture* 29.4 (2003), pp. 181–196.

[3]   P. Simpson and R. Van Bossuyt. "TREE-CAUSED ELECTRIC OUTAGES". In: *Journal of Arboriculture* 22 (1996), pp. 117–121.

[4]   Jason R. Parent, Thomas H. Meyer, John C. Volin, Robert T. Fahey, and Chandi Witharana. "An Analysis of Enhanced Tree Trimming Effectiveness on Reducing Power Outages". In: *Journal of Environmental Management* 241 (July 1, 2019), pp. 397–406.

[5] Roshanak Nateghi, Seth Guikema, and Steven M. Quiring. "Power Outage Estimation for Tropical Cyclones: Improved Accuracy with Simpler Models". In: *Risk Analysis* 34.6 (2014), pp. 1069–1078.

[6] Siegfried Guggenmoos. "Tree-Related Electric Outages Due To Wind Loading". In: *Arboriculture and Urban Forestry* 37.4 (2011), pp. 147–151.

[7] Shaun Wismer. *Targeted Tree Trimming Offers Reliability Benefits*. T&D World. May 16, 2018. URL: https://www.tdworld.com/vegetation-management/article/20971285/targeted-tree-trimming-offers-reliability-benefits (visited on 01/13/2021).

[8] E. Thomas Smiley, Nelda Matheny, and Sharon Lilly. *Best Management Practices - Tree Risk Assessment, Second Edition*. P1542. International Society of Arboriculture, 2017, p. 86.

[9] John W. Goodfellow. *Best Management Practices - Utility Tree Risk Assessment*. P1321. International Society of Arboriculture, 2020, p. 95.

[10] C. J. Rooney, H. D. Ryan, David V. Bloniarz, and B. Kane. "THE RELIABILITY OF A WINDSHIELD SURVEY TO LOCATE HAZARDS IN ROADSIDE TREES". In: *Journal of Arboriculture* 31.2 (2005).

[11] A. K. Koeser, D. C. McLean, G. Hasing, and R. B. Allison. "Frequency, Severity, and Detectability of Internal Trunk Decay of Street Tree Quercus Spp. in Tampa, Florida, U.S." In: *Arboriculture & Urban Forestry* 42.4 (2016), pp. 217–226.

[12] Pengcheng Jiao and Amir H. Alavi. "Artificial Intelligence in Seismology: Advent, Performance and Future Trends". In: *Geoscience Frontiers* 11.3 (May 1, 2020), pp. 739–744.

[13] Hadi Salehi and Rigoberto Burgueño. "Emerging Artificial Intelligence Methods in Structural Engineering". In: *Engineering Structures* 171 (Sept. 15, 2018), pp. 170–189.

[14] Billie F. Spencer, Vedhus Hoskere, and Yasutaka Narazaki. "Advances in Computer Vision-Based Civil Infrastructure Inspection and Monitoring". In: *Engineering* 5.2 (Apr. 1, 2019), pp. 199–222.

[15] Geoffrey A. Fricker, Jonathan D. Ventura, Jeffrey A. Wolf, Malcolm P. North, Frank W. Davis, and Janet Franklin. "A Convolutional Neural Network Classifier Identifies Tree Species in Mixed-Conifer Forest from Hyperspectral Imagery". In: *Remote Sensing* 11.19 (19 Jan. 2019), p. 2326.