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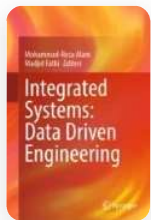
# Intelligent Lumber Production (Sawmill 4.0): Opportunities, Challenges, and Pathways to Adoption

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## [Integrated Systems: Data Driven Engineering](#)

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## Abstract

In transiting from automated to smart lumber manufacturing, the sawmilling industry should adopt cutting-edge technologies for efficient and cost-effective lumber production. This manuscript reviews the opportunities and challenges the sawmilling industry is facing

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to embrace a smart, data-driven manufacturing approach. Accordingly, the main steps in lumber manufacturing are introduced, and opportunities to practice smart production in sawmills, kilns, and planer mills are explained. Sawmills benefit from sensing and machine vision technology combined with artificial intelligence (AI) for efficient log breakdown, process health and equipment condition monitoring, and smart edging/trimming. The kiln drying process benefits from moisture pre- and post-sorting, in which nondestructive evaluation (NDE) of lumber moisture content is crucial. Smart lumber grading can be practiced using NDE-based techniques combined with AI. Despite the unprecedented opportunities, the lumber industry struggles to leverage big data analytics value and power. The advancement in the Internet of Things (IoT), cyber-physical systems, and cloud computing should highlight the importance of digital twins in sawmilling. AI and big data analytics will be used in the future, not just for smart quality control, processing monitoring, and optimization but for smart design and planning, material distribution and tracking, customization and flexible manufacturing, and market analysis and positioning.

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## References

1. Affonso, C., Rossi, A. L. D., Vieira, F. H. A., & de Leon Ferreira, A. C. P. (2017). Deep learning for biological image classification. *Expert Systems with Applications*, 85, 114–122.  
[Article](#) [Google Scholar](#)
2. Avramidis, S., Lazarescu, C., & Rahimi, S. (2023) Basics of wood drying. In *Springer handbook of wood science and technology* (pp. 679–706). Springer International Publishing. [https://doi.org/10.1007/978-3-030-81315-4\\_13](https://doi.org/10.1007/978-3-030-81315-4_13)

3. Ayanleye, S., Nasir, V., Avramidis, S., & Cool, J. (2021). Effect of wood surface roughness on prediction of structural timber properties by infrared spectroscopy using ANFIS, ANN and PLS regression. *European Journal of Wood and Wood Products*, 79, 101–115.

<https://doi.org/10.1007/s00107-020-01621-x>

[Article](#) [Google Scholar](#)

4. Belley, D., Duchesne, I., Vallerand, S., Barrette, J., & Beaudoin, M. (2019). Computed tomography (CT) scanning of internal log attributes prior to sawing increases lumber value in white spruce (*Picea glauca*) and jack pine (*Pinus banksiana*). *Canadian Journal of Forest Research*, 49(12), 1516–1524.

[Article](#) [Google Scholar](#)

5. Berberovic, A., & Milota, M. R. (2011). Impact of wood variability on the drying rate at different moisture content levels. *Forest Products Journal*, 61(6), 435–442.

[Article](#) [Google Scholar](#)

6. Berglund, A., Broman, O., Grönlund, A., & Fredriksson, M. (2013). Improved log rotation using information from a computed tomography scanner. *Computers and Electronics in Agriculture*, 90, 152–158.

[Article](#) [Google Scholar](#)

7. Bharati, M. H., MacGregor, J. F., & Tropper, W. (2003). Softwood lumber grading through on-line multivariate image analysis techniques. *Industrial and Engineering Chemistry Research*, 42(21), 5345–5353.

[Article](#) [Google Scholar](#)

8. Bond, B. H., & Espinoza, O. (2016). A decade of improved lumber drying technology. *Current Forestry Reports*, 2(2), 106–118.

[Article](#) [Google Scholar](#)

9. Byrne, G., Dornfeld, D., Inasaki, I., Ketteler, G., König, W., & Teti, R. (1995). Tool condition monitoring (TCM)—The status of research and industrial application. *CIRP Annals*, 44(2), 541–567.

[Article](#) [Google Scholar](#)

10. Cabardo, S. J. (2007). *Variability in physical and transport properties regarding drying behavior for regrowth and plantation blackbutt timber in New South Wales*. Ph.D. Dissertation, University of Sidney, South Wales, Australia.

[Google Scholar](#)

11. Cronin, K. P., Norton, B., & Taylor, J. (1997). Drying lumber in kilns: A methodology for stochastic analysis using Markov modeling. *Drying Technology*, 15(3–4), 765–790.

[Article](#) [Google Scholar](#)

12. Elustondo, D. M., & Avramidis, S. (2005). Comparative analysis of three methods for stochastic lumber drying simulation. *Drying Technology*, 23(1–2), 131–142.

[Article](#) [Google Scholar](#)

13. Elustondo, D., Avramidis, S., & Oliveira, L. (2005). Industrial evaluation of re-dry strategy for softwood lumber. *Maderas Ciencia y Tecnologia*, 7(2), 65–78.

[Google Scholar](#)

14. Elustondo, D., Oliveira, L., & Ananias, R. A. (2013). Visual method to assess lumber sorting before drying. *Drying Technology*, 31(1), 32–39.

[Article](#) [Google Scholar](#)

15. Fathi, H., Kazemirad, S., & Nasir, V. (2020). A nondestructive guided wave propagation method for the characterization of moisture-dependent viscoelastic properties of wood materials. *Materials and Structures*, 53, 1–14. <https://doi.org/10.1617/s11527-020-01578-6>

[Article](#) [Google Scholar](#)

16. Fathi, H., Nasir, V., & Kazemirad, S. (2020). Prediction of the mechanical properties of wood using guided wave propagation and machine learning. *Construction and Building Materials*, 262, 120848. <https://doi.org/10.1016/j.conbuildmat.2020.120848>

[Article](#) [Google Scholar](#)

17. Fredriksson, M. (2014). Log sawing position optimization using computed tomography scanning. *Wood Material Science and Engineering*, 9(2), 110–119.

[Article](#) [Google Scholar](#)

18. Fredriksson, M. (2016). Handling positioning errors when optimizing sawing of Scots pine and Norway spruce logs using CT scanning. *Journal of wood science*, 62(5), 400–406.

[Article](#) [Google Scholar](#)

19. Fredriksson, M., Berglund, A., & Broman, O. (2015). Validating a crosscutting simulation program based on computed tomography scanning of logs. *European Journal of Wood and Wood Products*, 73, 143–150.

20. Fredriksson, M., Wadsö, L., Johansson, P., & Ulvcrona, T. (2016). *Wood Material Science and Engineering*, 11(4), 189–200.

21. Fujimoto, T., Kurata, Y., Matsumoto, K., & Tsuchikawa, S. (2010). Feasibility of near-infrared spectroscopy for on-line grading of sawn lumber. *Applied Spectroscopy*, 64(1), 92–99.

22. Fujimoto, T., Kobori, H., & Tsuchikawa, S. (2012). Prediction of wood density independently of moisture conditions using near-infrared spectroscopy. *Journal of Near Infrared Spectroscopy*, 20(3), 353–359.

23. Galligan, W. L., & McDonald, K. A. (2000). *Machine grading of lumber: Practical concerns for lumber producers*. US Department of Agriculture, Forest Service, Forest Products Laboratory.

24. Gazo, R., Wells, L., Krs, V., & Benes, B. (2018). Validation of automated hardwood lumber grading system. *Computers and Electronics in Agriculture*, 155, 496–500.

25. Gazo, R., Vanek, J., Abdul\_Massih, M., & Benes, B. (2020). A fast pith detection for computed tomography scanned hardwood logs. *Computers and Electronics in Agriculture*,

26. He, T., Liu, Y., Xu, C., Zhou, X., Hu, Z., & Fan, J. (2019). A fully convolutional neural network for wood defect location and identification. *IEEE Access*, 7, 123453–123462.

[Article](#) [Google Scholar](#)

27. He, T., Liu, Y., Yu, Y., Zhao, Q., & Hu, Z. (2020). Application of deep convolutional neural network on feature extraction and detection of wood defects. *Measurement*, 152, 107357.

[Article](#) [Google Scholar](#)

28. Hu, J., Song, W., Zhang, W., Zhao, Y., & Yilmaz, A. (2019). Deep learning for use in lumber classification tasks. *Wood Science and Technology*, 53, 505–517.

[Article](#) [Google Scholar](#)

29. Ji, A., Cool, J., & Duchesne, I. (2021). Using X-ray CT scanned reconstructed logs to predict knot characteristics and tree value. *Forests*, 12(6), 720.

[Article](#) [Google Scholar](#)

30. Kline, D. E., Surak, C., & Araman, P. A. (2003). Automated hardwood lumber grading utilizing a multiple sensor machine vision technology. *Computers and Electronics in Agriculture*, 41(1–3), 139–155.

[Article](#) [Google Scholar](#)

31. Koponen, H. (1984). Dependences of moisture diffusion coefficients of wood and wooden panels on moisture content and wood properties. *Paperi ja puu*, 66(12), 740–

[Google Scholar](#)

32. Kusiak, A. (2017). Smart manufacturing must embrace big data. *Nature*, 544(7648), 23–25.

[Article](#) [Google Scholar](#)

33. Legg, B., Dorfner, B., Leavengood, S., & Hansen, E. (2021). Industry 4.0 implementation in US primary wood products industry. *Wood Industry/Drvna Industrija*, 72(2), 143–153.

[Google Scholar](#)

34. Li, H., Wang, L., Wang, B. J., Wei, P., Yu, W., Fan, Z., & Du, G. (2021). Preliminary evaluation of a density-based lumber grading method for hem-fir CLT manufacturing. *European Journal of Wood and Wood Products*, 79, 967–975.

[Article](#) [Google Scholar](#)

35. Licow, R., Chuchala, D., Deja, M., Orlowski, K. A., & Taube, P. (2020). Effect of pine impregnation and feed speed on sound level and cutting power in wood sawing. *Journal of Cleaner Production*, 272, 122833.

[Article](#) [Google Scholar](#)

36. Merela, M., Oven, P., Serša, I., & Mikac, U. (2009). A single point NMR method for an instantaneous determination of the moisture content of wood. *Holzforschung*, 63(3), 348–351.

[Article](#) [Google Scholar](#)

37. Mohammadpanah, A., & Hutton, S. G. (2015). Flutter instability speeds of guided splined disks: An experimental and analytical investigation. *Shock and Vibration*, 942141.

[Google Scholar](#)

38. Mohammadpanah, A., & Hutton, S. G. (2016). Maximum operation speed of splined saws. *Wood Material Science and Engineering*, 11(3), 142–146.

[Article](#) [Google Scholar](#)

39. Mohammadpanah, A., & Hutton, S. G. (2016). Dynamics behavior of a guided spline spinning disk, subjected to conservative in-plane edge loads, analytical and experimental investigation. *Journal of Vibration and Acoustics*, 138(4), 041005.

[Article](#) [Google Scholar](#)

40. Mohammadpanah, A., & Hutton, S. G. (2017) Theoretical and experimental verification of dynamic behaviour of a guided spline arbor circular saw. *Shock and Vibration*.

[Google Scholar](#)

41. Mohammadpanah, A., Lehmann, B., & White, J. (2019). Development of a monitoring system for guided circular saws: An experimental investigation. *Wood Material Science and Engineering*, 14(2), 99–106.

[Article](#) [Google Scholar](#)

42. Nasir, V., & Cool, J. (2019). Optimal power consumption and surface quality in the circular sawing process of Douglas-fir wood. *European Journal of Wood and Wood Products*, 77, 609–617. <https://doi.org/10.1007/s00107-019-01412-z>

[Article](#) [Google Scholar](#)

43. Nasir, V., & Cool, J. (2020). A review on wood machining: Characterization, optimization, and monitoring of the sawing process. *Wood Material Science & Engineering*, 15(1), 1–16. <https://doi.org/10.1080/17480272.2018.1465465>

[Article](#) [Google Scholar](#)

44. Nasir, V., & Cool, J. (2020). Intelligent wood machining monitoring using vibration signals combined with self-organizing maps for automatic feature selection. *The International Journal of Advanced Manufacturing Technology*, 108, 1811–1825. <https://doi.org/10.1007/s00170-020-05505-5>

[Article](#) [Google Scholar](#)

45. Nasir, V., & Cool, J. (2020). Characterization, optimization, and acoustic emission monitoring of airborne dust emission during wood sawing. *The International Journal of Advanced Manufacturing Technology*, 109(9–12), 2365–2375. <https://doi.org/10.1007/s00170-020-05842-5>

[Article](#) [Google Scholar](#)

46. Nasir, V., & Cool, J. (2021). Cutting power and surface quality in sawing kiln-dried, green, and frozen hem-fir wood. *Wood Science and Technology*, 55, 505–519. <https://doi.org/10.1007/s00226-020-01259-1>

[Article](#) [Google Scholar](#)

47. Nasir, V., & Sassani, F. (2021). A review on deep learning in machining and tool monitoring: Methods, opportunities, and challenges. *The International Journal of Advanced Manufacturing Technology*, 115(9–10), 2683–2709.  
<https://doi.org/10.1007/s00170-021-07325-7>
- [Article](#) [Google Scholar](#)
48. Nasir, V., Cool, J., & Sassani, F. (2019). Intelligent machining monitoring using sound signal processed with the wavelet method and a self-organizing neural network. *IEEE Robotics and Automation Letters*, 4(4), 3449–3456.  
<https://doi.org/10.1109/LRA.2019.2926666>
- [Article](#) [Google Scholar](#)
49. Nasir, V., Cool, J., & Sassani, F. (2019). Acoustic emission monitoring of sawing process: Artificial intelligence approach for optimal sensory feature selection. *The International Journal of Advanced Manufacturing Technology*, 102, 4179–4197.  
<https://doi.org/10.1007/s00170-019-03526-3>
- [Article](#) [Google Scholar](#)
50. Nasir, V., Kooshkbaghi, M., & Cool, J. (2020). Sensor fusion and random forest modeling for identifying frozen and green wood during lumber manufacturing. *Manufacturing Letters*, 26, 53–58. <https://doi.org/10.1016/j.mfglet.2020.09.011>
- [Article](#) [Google Scholar](#)
51. Nasir, V., Mohammadpanah, A., & Cool, J. (2020). The effect of rotation speed on the power consumption and cutting accuracy of guided circular saw: Experimental measurement and analysis of saw critical and flutter speeds. *Wood Material Science & Engineering*, 15(3), 140–146. <https://doi.org/10.1080/17480272.2018.1508167>

52. Nasir, V., Dibaji, S., Alaswad, K., & Cool, J. (2021). Tool wear monitoring by ensemble learning and sensor fusion using power, sound, vibration, and AE signals. *Manufacturing Letters*, 30, 32–38. <https://doi.org/10.1016/j.mfglet.2021.10.002>

53. Nasir, V., Kooshkbaghi, M., Cool, J., & Sassani, F. (2021). Cutting tool temperature monitoring in circular sawing: Measurement and multi-sensor feature fusion-based prediction. *The International Journal of Advanced Manufacturing Technology*, 112, 2413–2424. <https://doi.org/10.1007/s00170-020-06473-6>

54. Orłowski, K., Sandak, J., Negri, M., & Dzurenda, L. (2009). Sawing frozen wood with narrow kerf saws: Energy and quality effects. *Forest Products Journal*, 59(3), 79.

55. Rahimi, S. (2021). *Estimating the final moisture content variation in kiln-dried Pacific coast hemlock*. Doctoral dissertation, University of British Columbia.

56. Rahimi, S., & Avramidis, S. (2022). Predicting moisture content in kiln-dried timbers using machine learning. *European Journal of Wood and Wood Products*, 80(3), 681–692. <https://doi.org/10.1007/s00107-022-01794-7>

57. Rahimi, S., Faezipour, M., & Tarmian, A. (2011). Drying of internal-check prone poplar lumber using three different conventional kiln drying schedules. *Journal of the Indian Academy of Wood Science*, 8, 6–10. <https://doi.org/10.1007/s13196-011-0016-5>

[Article](#) [Google Scholar](#)

58. Rahimi, S., Avramidis, S., & Lazarescu, C. (2022a) Estimating moisture content variation in kiln-dried Pacific coast hemlock. *Holzforschung*, 76(1), 26–36. <https://orcid.org/0000-0001-6640-6626>

59. Rahimi, S., Nasir, V., Avramidis, S., & Sassani, F. (2022b). Wood moisture monitoring and classification in kiln-dried timber. *Structural Control and Health Monitoring*, 29(4), e2911. <https://doi.org/10.1002/stc.2911>

[Article](#) [Google Scholar](#)

60. Rahimi, S., Nasir, V., Avramidis, S., & Sassani, F. (2022c). Benchmarking moisture prediction in kiln-dried Pacific Coast hemlock wood. *International Wood Products Journal*, 13(4), 219–226. <https://doi.org/10.1080/20426445.2022.2104212>

[Article](#) [Google Scholar](#)

61. Rahimi, S., Nasir, V., Avramidis, S., & Sassani, F. (2023). The role of drying schedule and conditioning in moisture uniformity in wood: A machine learning approach. *Polymers*, 15(4), 792. <https://doi.org/10.3390/polym15040792>

[Article](#) [Google Scholar](#)

62. Rais, A., Pretzsch, H., & van de Kuilen, J. W. G. (2020). European beech log and lumber grading in wet and dry conditions using longitudinal vibration. *Holzforschung*, 74(10), 939–947.

63. Rosenkilde, A., & Glover, P. (2002). High resolution measurement of the surface layer moisture content during drying of wood using a novel magnetic resonance imaging technique. *Holzforschung*, 56, 312–317.

[Article](#) [Google Scholar](#)

64. Rosner, S., Riegler, M., Vontobel, P., Mannes, D., Lehmann, E. H., Karlsson, B., & Hansmann, C. (2012). Within-ring movement of free water in dehydrating Norway spruce sapwood visualized by neutron radiography. *Holzforschung*, 66(6), 751–756.

[Article](#) [Google Scholar](#)

65. Rummukainen, H., Makkonen, M., & Uusitalo, J. (2021). Economic value of optical and X-ray CT scanning in bucking of Scots pine. *Wood Material Science and Engineering*, 16(3), 178–187.

[Article](#) [Google Scholar](#)

66. Salas, C., & Moya, R. (2014). Kiln-, solar-, and air-drying behavior of lumber of *Tectona grandis* and *Gmelina arborea* from fast-grown plantations: Moisture content, wood color, and drying defects. *Drying Technology*, 32(3), 301–310.

[Article](#) [Google Scholar](#)

67. Schajer, G. S. (2001). Lumber strength grading using X-ray scanning. *Forest Products Journal*, 51(1), 43–50.

[Google Scholar](#)

68. Shahverdi, M., Oliveira, L., & Avramidis, S. (2017). Kiln-drying optimization for quality pacific coast hemlock lumber. *Drying Technology*, 35(15), 1867–1873.

[Article](#) [Google Scholar](#)

69. Tao, F., Qi, Q., Liu, A., & Kusiak, A. (2018). Data-driven smart manufacturing. *Journal of Manufacturing Systems*, 48, 157–169.

[Article](#) [Google Scholar](#)

70. Thomas, E. (2017). An artificial neural network for real-time hardwood lumber grading. *Computers and Electronics in Agriculture*, 132, 71–75.

[Article](#) [Google Scholar](#)

71. Thybring, E. E., & Fredrikson, M. (2023). Wood and moisture. *Springer handbook of wood science and technology* (pp. 355–398). Springer International Publishing.

[Chapter](#) [Google Scholar](#)

72. van Blokland, J., Nasir, V., Cool, J., Avramidis, S., & Adamopoulos, S. (2021). Machine learning-based prediction of internal checks in weathered thermally modified timber. *Construction and Building Materials*, 281, 122193.

<https://doi.org/10.1016/j.conbuildmat.2020.122193>

[Article](#) [Google Scholar](#)

73. van Blokland, J., Nasir, V., Cool, J., Avramidis, S., & Adamopoulos, S. (2021). Machine learning-based prediction of surface checks and bending properties in weathered thermally modified timber. *Construction and Building Materials*, 307, 124996.

<https://doi.org/10.1016/j.conbuildmat.2021.124996>

[Article](#) [Google Scholar](#)

74. Wang, S. Y., Chen, J. H., Tsai, M. J., Lin, C. J., & Yang, T. H. (2008). Grading of softwood lumber using non-destructive techniques. *Journal of Materials Processing Technology*, 208(1–3), 149–158.

[Article](#) [Google Scholar](#)

75. Wang, Y., Zhang, W., Gao, R., Jin, Z., & Wang, X. (2021). Recent advances in the application of deep learning methods to forestry. *Wood Science and Technology*, 55(5), 1171–1202.

[Article](#) [Google Scholar](#)

76. Watanabe, K., Lazarescu, C., Shida, S., & Avramidis, S. (2012). A novel method of measuring moisture content distribution in timber during drying using CT scanning and image processing techniques. *Drying Technology*, 30(3), 256–262.

[Article](#) [Google Scholar](#)

77. Watanabe, K., Hayashi, T., & Kobayashi, I. (2016). Probabilistic evaluation of the final moisture content of kiln-dried lumber using the bootstrap method. *Journal of Wood Science*, 62(6), 479–486.

[Article](#) [Google Scholar](#)

78. Williston, E. M. (1988). *Lumber manufacturing*. Forest Products Society.

[Google Scholar](#)

79. Wu, H., & Avramidis, S. (2006). Prediction of lumber kiln drying rates by neural networks. *Drying Technology*, 24(12), 1541–1545.

[Article](#) [Google Scholar](#)

80. Zhang, B. G., & Liu, D. Y. (2006). Exploring a new developing way of wood drying technology in China. *China Forest Products Industry*, 33(4), 3–6.

[Google Scholar](#)

81. Zhang, J., Cao, J., & Zhang, D. (2006). ANN-based data fusion for lumber moisture content sensors. *Transaction of the Institute of Measurement and Control*, 28(1), 69–79.

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