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Sommario/riassunto

Physics-Aware Machine Learning for Integrated Energy Systems Management, a new release in the Advances in Intelligent Energy Systems series, guides the reader through this state-of-the-art approach to computational methods, from data input and training to application opportunities in integrated energy systems.
