

1.	Record Nr.	UNIORUON00033865
	Titolo	MAPPAE arabicae : Arabische welt-und landerkarten des 9.-13. jahrhunderts in arabischer urschrift, lateinischer transkription und ubertragung in neuzeitliche kartenskizzen / mit einleitenden texten herausgegeben von Konrad Miller
	Pubbl/distr/stampa	Stuttgart, : Selbstverlag des herausgebers, 1926-1931 6 v. in 9, : ill. ; 30 cm Esempl. in fotocopia
	Classificazione	ARA VIII A
	Soggetti	CARTOGRAFIA - Medio Oriente - Sec. 9.-13 Geografia araba
	Lingua di pubblicazione	Tedesco
	Formato	Materiale a stampa
	Livello bibliografico	Monografia
2.	Record Nr.	UNINA9911048017403321
	Autore	Daneshvar Mohammadreza
	Titolo	Physics-Aware Machine Learning for Integrated Energy Systems Management
	Pubbl/distr/stampa	Chantilly : , : Elsevier, , 2025 ©2025
	ISBN	0-443-32985-0 0-443-32984-2
	Edizione	[1st ed.]
	Descrizione fisica	1 online resource (645 pages)
	Collana	Advances in Intelligent Energy Systems Series
	Altri autori (Persone)	Mohammadi-IvatlooBehnam ZareKazem AghaeiJamshid
	Disciplina	621.0420285631
	Lingua di pubblicazione	Inglese
	Formato	Materiale a stampa
	Livello bibliografico	Monografia

Front Cover -- Physics-Aware Machine Learning for Integrated Energy Systems Management -- Copyright Page -- Contents -- List of contributors -- 1 Attributes of integrated energy systems in modern energy grids -- Abbreviations -- 1.1 Introduction -- 1.2 Integrated energy system components and supplies -- 1.2.1 Solar energy in integrated energy systems -- 1.2.2 Energy storage in integrated energy systems -- 1.2.2.1 Electrical energy storage -- 1.2.2.2 Thermal energy storage -- 1.2.2.3 Mechanical energy storage -- 1.2.2.4 Electro-chemical energy storage -- 1.2.2.5 Chemical energy storage (power-to-gas) -- 1.3 Integrated energy system modeling tools and evaluation criteria -- 1.4 Integrated energy system management and optimization methodologies -- 1.4.1 Software tools -- 1.4.1.1 HOMER -- 1.4.1.2 GAMS -- 1.4.1.3 HYBRID2 -- 1.4.1.4 RET screen -- 1.4.2 Mathematical techniques -- 1.4.2.1 Metaheuristic algorithms -- 1.4.3 Machine learning technique -- 1.4.3.1 Artificial neural network -- 1.4.3.2 Decision trees -- 1.4.3.3 Support vector machines -- 1.4.3.4 K nearest neighbors -- 1.4.3.5 Linear regression -- 1.5 Attributes of modern integrated energy systems -- 1.6 Summary -- References -- 2 Physical-economic models for integrated energy systems management -- Abbreviations -- 2.1 Introduction -- 2.2.1 Distributed generation -- 2.2.1.1 Photovoltaic -- 2.2.1.2 Wind turbine -- 2.2.1.3 Fuel cell -- 2.2.2 Battery energy storage system -- 2.3.1 Objective function -- 2.3.1.1 The net present cost of distributed generations -- 2.3.1.2 Net present cost of purchased natural gas -- 2.3.1.3 Net present cost of penalty for environmental pollution -- 2.3.1.4 Net present cost of purchased electricity from electrical network -- 2.3.1.5 Net present cost of sold electricity to electrical network -- 2.3.1.6 Net present cost of penalty for load interruption. -- 2.3.2 Constraints -- 2.3.2.1 Power balance constraint -- 2.3.2.2 Electricity generation constraints -- 2.3.2.3 Battery energy storage system constraint -- 2.3.2.4 Purchased/sold power constraint -- 2.3.2.5 Reliability constraint -- 2.3.2.6 Renewable energy penetration -- 2.4.1 Generated electricity of wind turbines and photovoltaics can meet demand -- 2.4.2 Over generation -- 2.4.3 Over demand -- 2.4.3.1 Battery energy storage system adequacy for the demand satisfaction -- 2.4.3.1.1 Stored energy in battery energy storage system can satisfy demand -- 2.4.3.1.2 Available energy in battery energy storage system cannot satisfy demand -- 2.5 Proposed methodology -- 2.6 Simulation results -- 2.7 Conclusion -- References -- 3 Decision-making tools for optimal operation and planning of integrated energy systems -- Acronyms -- 3.1 An introduction to integrated energy system -- 3.2 Decision-making: a brief review -- 3.3 Multicriteria decision-making tools for the different conditions of integrated energy systems -- 3.3.1 Alternatives ranking -- 3.3.2 Weights of criteria determination -- 3.4 Integrated energy system performance metrics -- 3.5 Case study -- 3.5.1 Study framework -- 3.5.1.1 Best-worst method weighting method -- 3.5.1.2 Weighted aggregated sum product assessment ranking method -- 3.5.2 Results and discussion -- 3.6 Conclusion -- References -- 4 Energy storage in integrated energy systems: an efficient way to overcome the flexibility deficiency -- Nomenclature -- 4.1 An introduction to integrated energy system -- 4.2 Integrated energy system design and performance analysis -- 4.3 Energy storage for flexibility sufficiency -- 4.4.1 Study framework -- 4.4.1.1 Objective function -- 4.4.1.2 Constraints -- 4.4.1.2.1 Generation expansion planning constraints -- 4.4.1.2.2 Relating constraints -- 4.4.1.2.3 Unit commitment constraints. -- 4.4.2 Results and discussion -- 4.5 Conclusion -- References -- 5 Towards efficient energy management using intelligent prediction

models: a comparative study on energy consumption data -- Acronyms -- 5.1 Introduction -- 5.2 Related work -- 5.3 Methodology -- 5.3.1 Ensemble machine learning for regression -- 5.4 Model architecture -- 5.4.1 Multi-layer perceptron regressor -- 5.4.2 Random forest regressor -- 5.4.3 Extra trees regressor -- 5.4.4 Support vector regression -- 5.4.5 Averaging meta-regressor -- 5.5 Results and discussion -- 5.5.1 Dataset overview -- 5.5.2 Evaluation of single regressors -- 5.5.3 Evaluation of ensemble models -- 5.5.4 Comparison between various prediction algorithms -- 5.5.5 Discussion and analysis -- 5.5.6 Energy consumption surveillance framework: a blockchain-based neighborhood energy consumption model -- 5.6 Conclusion -- Acknowledgment -- References -- 6 Application of machine learning techniques in managing integrated energy systems -- Acronyms -- 6.1 Integrated energy system management -- 6.2.1 Multiagent deep deterministic policy gradient -- 6.2.2 Twin delayed deep deterministic policy gradient (TD3) based deep reinforcement learning -- 6.2.3 Automated deep reinforcement learning -- 6.2.4 Bidirectional generative adversarial network -- 6.2.5 Transfer learning -- 6.2.6 Deep multitask learning -- 6.2.7 Wavelet neural network -- 6.2.8 Multi-kernel extreme learning -- 6.2.9 Radial basis function neural network -- 6.2.10 Bidirectional gated recurrent unit -- 6.3 Machine learning in reliability assessment of integrated energy system -- 6.4 Resilience assessment for integrated energy system -- 6.5.1 Evolutionary imitation curriculum-Multiagent deep deterministic policy gradient for load frequency control -- 6.5.2 TD3-based deep reinforcement learning for load frequency control. 6.6.1 Machine learning in integrated energy system day-ahead scheduling -- 6.6.2 Machine learning in integrated energy system real-time scheduling -- 6.6.3 Machine learning in integrated energy system intra-day scheduling -- 6.6.4 Machine learning in integrated energy system long-term scheduling -- 6.7.1 Machine learning in dynamic dispatch of integrated energy system -- 6.7.2 Machine learning in economic dispatch of integrated energy system -- 6.8 Machine learning application in integrated energy system load forecasting -- 6.9 Fault detection -- 6.10 Conclusion -- References -- 7 Physics-aware machine learning for energy management of integrated energy systems -- Acronyms -- 7.1 Introduction -- 7.2.1 Energy input structure -- 7.2.1.1 Renewable electrical energy -- 7.2.1.2 Gas input energy -- 7.2.2 Energy hub equipment -- 7.2.2.1 Combined heat and power -- 7.2.2.2 Heating equipment -- 7.2.2.3 Cooling equipment -- 7.2.2.4 Energy storage equipment -- 7.2.3 Multienergy system networks -- 7.2.4 Integrated energy system output structure -- 7.2.4.1 Cogeneration -- 7.2.4.2 Trigeneneration -- 7.2.4.3 Polygeneration -- 7.3.1 Supervised, unsupervised, and reinforcement learning -- 7.3.2 Online learning -- 7.3.3 Transfer learning -- 7.3.4 Deep learning -- 7.3.5 Decision trees -- 7.3.6 Support vector machines -- 7.3.7 Ensemble learning -- 7.3.8 Bayesian models and Gaussian processes -- 7.4 What is physics-aware machine learning? -- 7.5.1 Solar and wind power estimation -- 7.5.1.1 Predicting the output power of wind systems -- 7.6.1 Building energy hub -- 7.6.2 Polygeneration microgrid energy hub -- 7.6.3 Electric vehicles-energy hub -- 7.6.4 Energy community manager -- 7.7 Conclusion -- References -- 8 Machine learning-based methods for carbon emissions management in integrated energy systems -- Acronyms -- 8.1.1 Motivation and background. 8.1.2 Main objectives and structure -- 8.2.1 Carbon management importance -- 8.2.2 Carbon management definition -- 8.2.3 Carbon footprint concept -- 8.2.4 Carbon trading and markets -- 8.3.1 The

production of hydrogen through biomass gasification combined with carbon capture and storage -- 8.3.1.1 Biomass gasification -- 8.3.1.2 Hydrogen separation -- 8.3.1.3 Carbon capture and storage -- 8.3.1.4 Negative emissions -- 8.3.1.5 Integration with renewable energy systems -- 8.3.2 Bioenergy with carbon capture and storage -- 8.3.3 Direct air carbon capture and storage in integrated energy system -- 8.3.4 Circular economy initiatives with goal of carbon management -- 8.3.5 Smart grid technologies -- 8.3.6 Carbon footprint assessment -- 8.3.6.1 Life cycle assessment -- 8.3.6.2 Carbon emission tracking -- 8.3.6.3 Carbon trading -- 8.4.1 Bioenergy with carbon capture and storage with applying machine learning -- 8.4.1.1 Optimizing biomass growth -- 8.4.1.2 Enhancing carbon capture processes -- 8.4.1.3 Energy production forecasting -- 8.4.2 Application of artificial intelligence and machine learning in direct air carbon capture and storage -- 8.4.2.1 Material discovery -- 8.4.2.2 Process optimization and data analysis -- 8.4.3 Machine learning in life cycle assessment -- 8.4.4 Carbon emissions tracking and monitoring -- 8.4.5 Carbon trading and carbon market -- 8.5 Findings and discussion -- References -- 9 Physics-aware machine learning for sustainable development of integrated energy systems -- Nomenclature -- 9.1 Introduction -- 9.2 Literature review -- 9.3 Data-driven optimal power flow based on the physics-aware machine learning approach in integrated energy systems -- 9.4.1 Role of machine learning methods in integrated energy systems -- 9.4.2 Physics-aware machine learning applications for sustainable development of integrated energy systems. 9.4.3 Smart energy systems for green energy goals.

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.
