Operation Orchestration of Local Energy Communities through Digital Twin: A Review on suitable Modeling and Simulation Approaches

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***Abstract*—Increasing the integration of distributed energy resources (DERs) requires an orchestration of the existing centralized management system used for the electricity grid and the emerging distributed ones for local energy communities (LEC). To support this orchestration, design and operation strategies of LECs needs to be analysed, based on a so-called Digital Twin (DT) platform with suitable modeling and simulation techniques. This paper presents a set of requirements needed to develop DT, thus enabling operation orchestration of LECs. Based on these specific requirements, a comprehensive review on the relevant physics-based and data-driven models will be discussed, especially focusing on the flexibility profile of LEC based on data-driven model to support the balancing reserves to the electricity grid.**

***Index Terms*—Digital twin, Local Energy Community, physics-based model, data-driven model, flexibility profile.**

I. Introduction

Electrical energy systems worldwide are under a rapid transformation as a result of technological changes, and ambition to achieve the target of climate neutrality. The increase of small-scale, environmental-friendly distributed energy resources (DERs), e.g., solar photovoltaic (PV), wind turbine, battery systems (BESS), electric vehicles (EVs), or heat pumps (HPs) requires the change of the centralized paradigm to manage the electrical energy systems to evolve toward distributed ones which are adopted for local energy communities (LEC). In Fig. 1, each LEC represents a locally and collectively organized energy system that consists of a number of houses and/or buildings, and have a variety of local generations of heat and electricity, flexible storage systems and demands. LEC is not only capable of self-provision of energy, but also sharing resources with other LECs to make efficient use of most energy available, and contribute to ancillary services such as balancing reserves, reactive power supporting.

Due to the diversity of sub-systems included (integrated buildings with on-site DERs within the LEC), an orchestration between LECs and the electricity grid is crucial to harmonise various management and operational objectives. To enable such the orchestration, Digital twin (DT) has emerged as a promising approach to reflect the best models with real-time updated information to emulate the complete characteristics, actions, operations, as well as life cycle of actual systems with potential services [1]. It is based on selecting proper modeling and simulation tools to capture fully steady-state and dynamic behaviours of each component and the overall integrated systems. The existing modeling approaches and simulation tools have focused either electricity networks or local energy systems, while interaction between these two systems (e.g., utility grid vs. LEC) is not comprehensively addressed. There are some works done to fill in this gap, e.g., NEPLAN [2], DEMKit [3], which provides tools to analyze, plan, optimize and simulate large-scale electrical networks. However, these tools are only for case specific while the generic approach is missing to replicate in large system areas, with the possibility for various services, such as demand respond programs, or market structures.

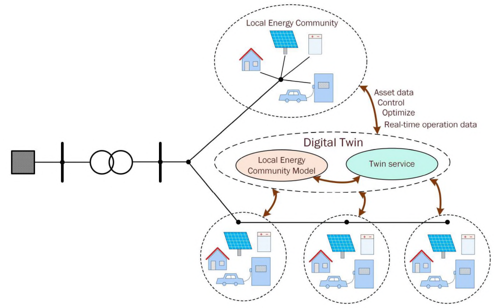

Fig. 1. LEC and electricity grid through Digital Twin.

In this paper, we specify on requirements needed to develop a DT platform to enable the orchestration of LECs and the electricity networks. A comprehensive review on the current state of the art (SotA) in modeling and simulations for integrated energy systems (electricity grids and LECs) will be conducted to find a suitable approach so that the local control strategies available for sub-systems (building, building neighborhood) will be listed and reflected on available modeling approaches.

Firstly, a possible DT framework for a LEC is presented in Section II. Then, the current SotA modeling and simulation tools is shown in Section III. Section IV shows the mapping of the DT requirements to available modeling approaches.

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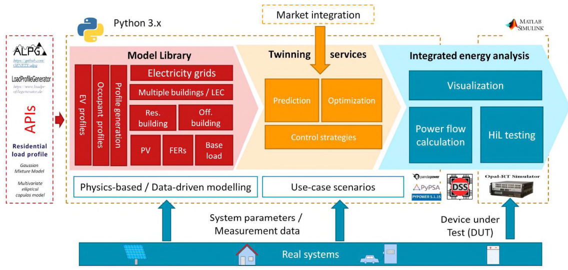

Fig. 2. Digital twin framework for Local Energy Community.

II. Digital twin framework for LEC

In this paper, we present a possible framework for DT platform, focusing on a virtual testing environment for a specific LEC located in the Bunnik, the Netherlands, as shown in Fig. 2. This environment represents (almost) identical characteristics as the real system; and includes model library, twining services, and the integrated energy analysis. The developed platform is essential for assessing the value and profitability of energy communities, and optimisation of the (system) design. Being considered as a living lab, the LEC in Bunnik has 8 office buildings including PV rooftop systems, EV charging stations, BESS connected in a ring network topology through some medium voltage (MV)/low voltage (LV) transformers. Through a bi-directional exchange of information between the virtual testing and physical environment, the efficiency of both systems is continuously enhanced.

A. Model library

The developed library contains various (physics-based and/or data-driven) component models to build and examine exactly the behaviors of both components and complete LECs. The developed library enables four modeling levels, including components level (PV, FERs, base load), building level (residential building, office building), multiple building/LEC level, and electricity grids level. Depending on the applications, the physics-based models are formulated mathematically in detailed or simplified approaches. Thanks to the cutting-edge Artificial Intelligence (AI) technologies, behaviors which are difficult to model by physics-based model can be captured by data-driven models or a combination of these methods, using machine learning techniques taking into account historical data. In the model library, the LEC profiles (PV, base-load, flexibility) are generated by leveraging some existing application programming interfaces (APIs) such as Artificial Load Profile Generator (ALPG) [4], Load Profile Generator [5], Residential load profile based on gaussian mixture model [6] or multivariate elliptical copulas model [7]. The model library is developed in Python open source to facilitate replication both in academia and industry.

B. Twining Services

The twining services provide different functionalities to develop control strategies for included sub-systems (e.g., buildings or building neighbourhoods) to analyse and optimize their coordination, e.g., automatic frequency restoration reserve (aFRR). The twining services are developed based on

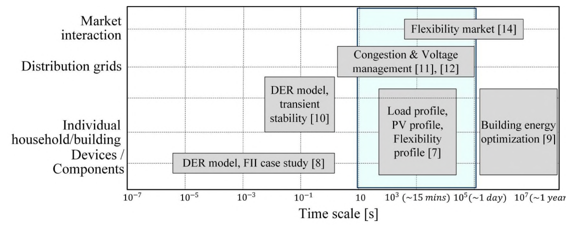

Fig. 3. Twining services considering in Time scale dimension.

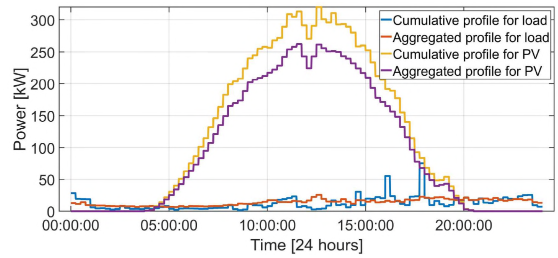

Fig. 4. Load and PV profile of a LEC.

several objectives, such as minimize costs, maximize the penetration of renewable energy resources and minimize energy consumption. In this part, market integration is one of the important factors that should be considered in this platform to develop the control strategies. For instance, the market price information from the electricity market is used in aFRR service to maximize profit of LEC and optimize the performance of BESS.

C. Integrated energy analysis

The outputs of the twining services are the profiles of LEC, buildings, or components. Based on these outputs, the integrated energy analysis is developed for different stakeholder purposes. The energy analysis can be done by various developed power flow calculation depending on the purpose of the analysis and the complexity of the systems. Another option is considering open sources such as OpenDSS, Pandapower, Pypsa, Pypower. Hardware-in-the-loop testing environment is used to implement validation of the developed models and control strategies in a real-time digital simulator named OPAL-RT platforms connecting with the Matlab software. Lastly, the visualization module will be developed in our platform to deliver the results to end-users.

D. Modeling and Simulation Requirements

To employ the DT platform for orchestrating operation of LEC and the electricity grid, there is a variety of requirements that need to be taken into account. The hypothetical LEC consists of 10 to 100 houses and/or buildings, with aggregated PV systems in a range of 100 kW - 300 kW, and flexible energy resources (FERs) such as BESS, EVs, and EV charging stations, heat pump systems. The LEC is normally connected to the electricity grid through a transformer 22/0.4 kV, as depicted in Fig. 1.

Besides the aspects of system and profile data requirements, the time scale dimension (see Fig. 3) is also one of the important factors that needs to be considered for setting up a DT platform. Depending on the analytical needs of the stakeholders, the DT platform can be developed to model different

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levels, ranging from component [8], household/building [7], [9], and complete LEC level [10], to distribution [11], [12], and grid/market interaction level [13]. Each modeling level corresponds to a specific time-scale frame (from microsecond to years or longer). In the future work, we will focus on the highlighted area (the quasi-dynamics time scale) to investigate scenarios and optimal algorithm for DER control and coordination, building(s) and LEC energy management to show the flexibility value, peak reduction, optimal energy consumption within LEC based on DT platform.

In Fig. 4, PV and load profiles for an individual household and the aggregated community are presented that a residential area will generate a lot of energy during the day and especially consume energy in the evening. The individual household profile or the aggregated profile of the LEC are modeled using a day data with 15-minute resolution. The blue and yellow lines represent the total power consumption and PV generation of 55 households in a LEC assuming the households have the same consumption and PV generation data, respectively. However, in practice, if there is enough data from the smart meter, the red and purple lines illustrate accurately the total power consumed and PV generation from these households, respectively. There is a relative difference between the actual measured data and the assumption of lack of data. In fact, PVs in each house are installed in the same geographical area where are the same weather conditions (irradiance, temperature). However, because each installed PV capacity is different in each house, so the PV generation is not equal. This shows the importance of the data-driven model in implementing DT platforms. In addition, the load and PV profiles of LEC also show a surplus generated from PV that has not been fully utilized in households. This enables the twining services of the LEC to be able to make the most of this surplus energy, such as providing balancing reserves [13]–[16] or exchanging energy [17]–[19] to other LECs.

III. Review on Modeling Approaches

Due to the diversity of network configurations and involved components, it is hard to find a unique, general representation of LECs. There are various modeling approaches in the literature that can be applied to model LECs. The following section aims to review different aspects of available modeling and simulation techniques, tools that are useful for the development of LEC Digital Twin models.

A. Physics-based Model

The classical approach uses mathematical representations of physical systems to derive the components and the whole LEC model. Herewith, it is classified as physics-based model. In this approach, usually, each component of LEC is modelled by component-based approach, then aggregated to obtain a complete LEC model. The mathematical model of each component is obtained based on detailed knowledge of actual devices. Then, a high order state space model, which can be represented for most engineering systems, is used to simulate a complete LEC in a standard form as follows:

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) \\ y(t) &= Cx(t) + Du(t) \end{aligned} \tag{1}$$

where $x(t), y(t), u(t)$ are the vectors of system state, output, and input; A, B, C, D are the matrices of state, input and output, and feed-forward.

The complexity of aggregated models can be reduced by applying simplification techniques, such as order reduction methods, or neglecting several dynamics of the system that are not necessary for certain research purposes. Several applications of this type of model for DERs can be found in [8], [10], [11], [20], [21]. In [11], [20], one-year time-series power flow is executed using OpenDSS platform to calculate state variables such as voltage magnitude, currents and powers in LEC based on physics-based model. Authors in [8], [10], [22] proposed coupled sequence components based models of DER, load devices to conduct the transient stability analysis of LEC. The proposed component-based models of DERs can reflect the behavior of actual systems with a high level of detail which reduce computational time while maintaining accurate dynamics.

In most power system studies, static load models such as constant impedance/current/power, ZIP or exponential models which provide adequate accuracy for steady-state or semi steady-state studies. However, the static models have a disadvantages of less accuracy in capturing the transient dynamics of the power electronic load devices.

FERs, including BESS, plug-in EVs, thermal (TESS) and hydrogen (HESS) energy storage systems, are essential components for flexible and reliable operations of LECs. Typically, BESS [23], [24] and storage system of EVs [25] can be modeled as (nonlinear or linear) equivalent circuit model [26], or electrochemical model in term of their state of charge [27]. Similar to BESS, TESS and HESS can be modeled in term of thermal balance [28] and level of stored hydrogen [29], respectively.

The electricity grid can be modeled in various ways, depending on the purposes of system analyses. Electrical networks can be modeled as equivalent (multi-) port networks using network and port theory [30], or equivalent models using the Thevenin theorem [31]. In [32], [33], the state-space model of a multi-bus electrical network is developed through linearization of equations describing components in the system, including power electronics-based converters, controllers, electrical topology of the system described by nodal admittance matrix, and impedance-equivalent load models. These models can be used to evaluate system stability and performance, as well as component-, system-level controller designs.

B. Data-driven Model

It is known that a formulation of mathematical models requires detailed knowledge of the actual system (including steady-state, dynamics behavior and uncertainties), hence not being applicable for LEC with a complex structure. The integration of information and communication technologies, and

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advanced measurement infrastructure enables the development of data-driven approaches that can satisfy the growing demand for accurate, scalable LEC modeling.

Accurate data-driven modeling approaches for DERs (PV, Wind turbine) are discussed in [34], [35], in which the models are design based on only representative sub-datasets from large DER input data, selected by a crucial pre-processing step. By doing this way, extreme large amount of unnecessary computation is reduced while the completeness and accuracy of the developed models is still guaranteed. Furthermore, the direct forecasting model for PV power generation is developed directly using PV power output historical data samples is discussed in [36].

The EV charging stations can be represented by stochastic models, as proposed in [37]–[39]. These models also include uncertainties, such as charging classes, charging load profiles, and location of the EVs. The high accuracy of these models allows various studies for grid supporting services of these flexible resources.

To enhance the static load models, proper stochastic modeling of load consumption is required in different types of studies such as modern grid planning, quantification of impact of low carbon technologies, finding secure levels of penetration of PV generation, and LV state estimation as in [7], [40]–[42]. The main purpose of these approaches is to capture the statistical properties of the smart meter measurement dataset to generate the load profiles.

For electrical networks, dynamic equivalent models using measurement data are powerful modeling approaches that can be used for various applications [43]. The Prony analysis [44], and System identification technique [45] use the input and output measurement data to generate a black-, grey-box models of the system structure without requiring full knowledge of system structure and parameters.

As an example, a general architecture of Deep Reinforcement Learning (DRL) to optimize the electricity consumption of devices in residential buildings and aggregations of buildings is shown in [9]. The combination of Reinforcement Learning and Deep Neural Network enables powerful models for the online cost minimization problem in a large systems with high uncertainties of electrical patterns.

In [7], the authors proposed a top-down data-driven modeling approach named conditional multivariate elliptical copulas for generating the resident load profiles in quasi-dynamic time frame. The proposed approach unifies the consumption modeling for MV and LV networks, simulating active power consumption scenarios in flexible time horizons for a whole year. Based on a one-year smart meter data, the power flow analysis generates training data sets for a data-driven state estimation for LEC requiring more accurate and lower computational burden in [46]. The state estimation was designed based on the physical connections of the distribution network and the position of the phasor measurement unit (PMU). The authors in [47] presented a probabilistic approach for grid supportive demand side management based on Monte Carlo as well as Neural Network method to reduce the probability of geographical dependent operation limit violations considering in quasi-dynamic time domain. In [48], a stochastic optimization model is used for the optimal operation for an LEC. The mixed-integer linear programming (MILP) model minimizes both the operation cost and CO_2 emission of LEC which is run with a one-hour time resolution for one day. The MILP model was implemented and solved in AMPL and CPLEX. An online state of charge and state of health estimation of BESS [49] is explored by DT platform with equivalent circuit models and all battery relevant data measured and transmitted to the cloud thank to the Internet of Energy.

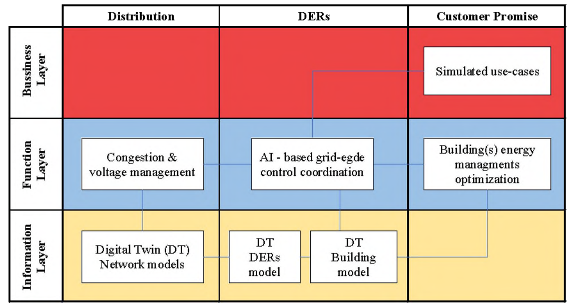

Fig. 5. Digital Twin architecture built in SGAM model.

IV. Mapping the Requirements of Digital Twin to Available Modeling

Most of the related articles using the DT platform focus on individual applications, the operation orchestration between the LEC and the grid has not been taken into account [50]–[54]. In order to orchestrate the operation of LEC and the electricity grid through DT, the mapping of a variety of requirements discussed in Section II with current SotA model and simulation tools is essential. Table I illustrates a classification of SotA studies on LEC and DERs through DT and conventional approach.

The peak load shaving use case [55] includes three main strategies which are demand-side management, BESS and EV integration between LEC and the electricity grid. The optimization and control models for peak load shaving strategies are implemented both in the data-driven model [56] and the physics-based model [57]. In order to perform peak load shaving strategies, various requirements of system characteristics are detailed in table I, including the number of houses, the total of PV generation, FER parameters, network topology, as well as measurement data in 15 minutes resolution. The remaining use cases, including building load forecasting, self-sufficiency scheduling, balancing reserve, congestion and voltage management, and smart mobility charging station, take into account additional requirements, depending on the coupling features of the use-cases, e.g., occupancy levels or thermal conversions. The profile requirements, besides data from smart meter, important data such as weather condition, cost rate, and assigned data from transmission/distribution system operators (TSO, DSOs) are also considered in DT platform for LEC.

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TABLE I
MAPPING REQUIREMENTS FOR EACH DT USE-CASES TO RELEVANT MODELING AND SIMULATIONS METHODS

Use cases of DT	Requirements		Modeling/ Simulation tools	
	System	Profile	Data-driven models	Physics-based models
Peak load shaving	• 10 - 100 households • 100 - 300 kWp PV • FERs: BESS, EV, HP • 22/0.4kV grid topologies	• Smart meter data • EV pattern profiles • Radiance profiles • Temp. profiles	[56]	[57]
Building load and production forecasting	• Building features • 10 - 100 kWp PV • FERs: BESS, EV, HP • Thermal conversions	• Smart meter data • EV pattern profiles • Occupancy profiles	[1], [7], [17], [19], [36], [40]	[1], [17], [19]
Building/LEC self-sufficiency	• Building features • 10 - 100 kWp PV • FERs: BESS, EV, HP • Thermal conversions	• Forecasted building load data • EV pattern profiles • Forecasted PV profiles	[41], [45], [48]	[48]
Balancing reserve	• Building features • 10 - 300 kW/kWh BESS • Building thermal inertia	• Assigned data from TSO • Scheduled energy profiles	[13]–[15], [21]	[13]–[15], [21]
Congestions and Voltage management	• 10 - 100 households • 100 - 300 kWp PV • FERs: BESS, EV, HP • 22/0.4kV grid topologies	• Assigned data from DSO • Weather data	[11]	[20]
Smart charging	same as above	• Market price data • Network residual capacity data • EV pattern profile data	[25], [37], [39], [52]	[26], [27], [38]

In TROEF project, the architecture of DT platform is designed in the smart grid architecture model (SGAM) [58], including three layers as shown in Fig. 5. The Information layer consists of network models (quasi-dynamic models of network assets, e.g., transformers, cable lines, network topologies), DER models (on-site PV, wind, batteries, EV charging and associated parameters), and building models (e.g., thermal-electric models of buildings with potential flexibility gained from thermal mass). The functional layer has various different use–cases for residential building, building-related generation systems, controllable building installations, utility building, electric mobility impact, analyzing potential problem of congestion and voltage management in distribution system, AI-based DER coordination, and building(s) energy management optimization. The business layer aims to develop DT platform with the involvement of business actors such as solution or algorithm developers, building owner or operators, local authorities (e.g., municipalities), distribution system operator. Based on system and data requirements for the development of DT platform, it is possible to apply and improve the current SotA model and simulation tools to fulfill the technical requirements proposed in the SGAM model of TROEF project.

V. CONCLUSION

This papers aims to present an overview about possible modeling and simulation methods needed while considering the integration between Local energy community (LEC) and the electricity grid through Digital Twin (DT) platform. The analysis specifies on the requirements needed for developing a Digital Twin platform which enables the operation orchestration between the LEC and the electricity grid. Based on this development of DT, generating individual household/building profiles as well as the aggregated ones for LECs play a crucial role which can be realized via either physics-based or data-driven models. In the future work, this topic will be addressed comprehensively along with potential flexibility from the LEC which can provide balancing reserves to the electricity grid.

REFERENCES

[1] E. O'Dwyer, I. Pan, R. Charlesworth, S. Butler, and N. Shah, "Integration of an energy management tool and digital twin for coordination and control of multi-vector smart energy systems," *Sustainable Cities and Society*, vol. 62, nov 2020.

[2] [Online]. Available: https://www.neplan.ch/

[3] G. Hoogsteen, J. L. Hurink, and G. J. Smit, "DEMKit: A Decentralized Energy Management Simulation and Demonstration Toolkit," *Proceedings of 2019 IEEE PES Innovative Smart Grid Technologies Europe, ISGT-Europe 2019*, pp. 13–17, 2019.

[4] G. Hoogsteen, A. Molderink, J. L. Hurink, and G. J. Smit, "Generation of flexible domestic load profiles to evaluate demand side management approaches," in *2016 IEEE International Energy Conference (ENERGYCON)*. IEEE, 2016, pp. 1–6.

[5] N. Pflugradt, J. Teuscher, B. Platzer, and W. Schufft, "Analysing low-voltage grids using a behaviour based load profile generator," in *International conference on renewable energies and power quality*, vol. 11, 2013, p. 5.

[6] G. J. McLachlan, S. X. Lee, and S. I. Rathnayake, "Finite mixture models," *Annual review of statistics and its application*, vol. 6, pp. 355–378, 2019.

[7] E. M. S. Duque, P. P. Vergara, P. H. Nguyen, A. Van Der Molen, and J. G. Slootweg, "Conditional Multivariate Elliptical Copulas to Model Residential Load Profiles from Smart Meter Data," *IEEE Transactions on Smart Grid*, vol. 12, no. 5, pp. 4280–4294, sep 2021.

[8] M. H. Roos, P. H. Nguyen, J. Morren, and J. G. Slootweg, "Modeling and Experimental Validation of Power Electronic Loads and DERs for Microgrid Islanding Simulations," *IEEE Transactions on Power Systems*, vol. 35, no. 3, pp. 2279–2288, may 2020.

[9] E. Mocanu, D. C. Mocanu, P. H. Nguyen, A. Liotta, M. E. Webber, M. Gibescu, and J. G. Slootweg, "On-line building energy optimization using deep reinforcement learning," *IEEE transactions on smart grid*, vol. 10, no. 4, pp. 3698–3708, 2018.

[10] M. Roos, P. Nguyen, J. Morren, and J. G. Slootweg, "Direct-Quadrature Sequence Models for Energy-Function Based Transient Stability Analysis of Unbalanced Inverter-Based Microgrids," *IEEE Transactions on Smart Grid*, vol. 12, no. 5, pp. 3692–3704, sep 2021.

[11] T. T. Mai, A. N. M. Haque, P. P. Vergara, P. H. Nguyen, and G. Pemen, "Adaptive coordination of sequential droop control for pv inverters to mitigate voltage rise in pv-rich lv distribution networks," *Electric Power Systems Research*, vol. 192, p. 106931, 2021.

[12] P. P. Vergara, T. T. Mai, A. Burstein, and P. H. Nguyen, "Feasibility and Performance Assessment of Commercial PV Inverters Operating with Droop Control for Providing Voltage Support Services," in *Proceedings of 2019 IEEE PES Innovative Smart Grid Technologies Europe, ISGT-Europe 2019*. Institute of Electrical and Electronics Engineers Inc., sep 2019.

[13] S. F. Contreras, C. A. Cortes, and J. M. Myrzik, "Optimal microgrid planning for enhancing ancillary service provision," *Journal of Modern Power Systems and Clean Energy*, vol. 7, no. 4, pp. 862–875, 2019.

[14] Y. Zhou, Z. Wei, G. Sun, K. W. Cheung, H. Zang, and S. Chen, "A robust optimization approach for integrated community energy system in energy and ancillary service markets," *Energy*, vol. 148, pp. 1–15, 2018.

[15] H. Firoozi, H. Khajeh, and H. Laaksonen, "Optimized operation of local energy community providing frequency restoration reserve," *IEEE Access*, vol. 8, pp. 180558–180575, 2020.

[16] R. Rana, K. Berg, M. R. Brubæk, and O. B. Fosso, "Ancillary services from a residential community-a norwegian case study," in *2021 International Conference on Smart Energy Systems and Technologies (SEST)*. IEEE, 2021, pp. 1–6.

[17] R. Faia, J. Soares, T. Pinto, F. Lezama, Z. Vale, and J. M. Corchado, "Optimal model for local energy community scheduling considering peer to peer electricity transactions," *IEEE Access*, vol. 9, pp. 12420–12430, 2021.

[18] E. Kremers, "Intelligent local energy management through market mechanisms: Driving the german energy transition from the bottom-up," *Energy Reports*, vol. 6, pp. 108–116, 2020.

978-1-6654-7982-0/22/$31.00 ©2022 IEEE

[19] M. Stephant, D. Abbes, K. Hassam-Ouari, A. Labrunie, and B. Robyns, "Distributed optimization of energy profiles to improve photovoltaic self-consumption on a local energy community," *Simulation Modelling Practice and Theory*, vol. 108, p. 102242, 2021.

[20] P. P. Vergara, T. T. Mai, A. Burstein, and P. H. Nguyen, "Feasibility and Performance Assessment of Commercial PV Inverters Operating with Droop Control for Providing Voltage Support Services," in *Proceedings of 2019 IEEE PES Innovative Smart Grid Technologies Europe, ISGT-Europe 2019*. Institute of Electrical and Electronics Engineers Inc., sep 2019.

[21] M. Roos, D. Geldtmeijer, H. Nguyen, J. Morren, and J. Slootweg, "Optimizing the technical and economic value of energy storage systems in lv networks for dno applications," *Sustainable Energy, Grids and Networks*, vol. 16, pp. 207–216, 2018.

[22] M. H. Roos, P. H. Nguyen, J. Morren, and J. Slootweg, "Aggregation of component-based grid-feeding der and load models for simulation of microgrid islanding transients," *Electric Power Systems Research*, vol. 189, p. 106759, 2020.

[23] C. Parthasarathy, H. Hafezi, and H. Laaksonen, "Lithium-ion bess integration for smart grid applications-ecm modelling approach," in *2020 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT)*. IEEE, 2020, pp. 1–5.

[24] T.-A. Nguyen-Huu, V. T. Nguyen, K. Hur, J. W. Shim *et al.*, "Coordinated control of a hybrid energy storage system for improving the capability of frequency regulation and state-of-charge management," *Energies*, vol. 13, no. 23, p. 6304, 2020.

[25] G. Piazza, S. Bracco, F. Delfino, and S. Siri, "Optimal design of electric mobility services for a local energy community," *Sustainable Energy, Grids and Networks*, vol. 26, p. 100440, 2021.

[26] A. Farmann and D. U. Sauer, "Comparative study of reduced order equivalent circuit models for on-board state-of-available-power prediction of lithium-ion batteries in electric vehicles," *Applied Energy*, vol. 225, pp. 1102–1122, sep 2018.

[27] J. Schmalstieg, C. Rahe, M. Ecker, and D. U. Sauer, "Full Cell Parameterization of a High-Power Lithium-Ion Battery for a Physico-Chemical Model: Part I. Physical and Electrochemical Parameters," *Journal of The Electrochemical Society*, vol. 165, no. 16, pp. A3799–A3810, 2018.

[28] G. Alva, Y. Lin, and G. Fang, "An overview of thermal energy storage systems," *Energy*, vol. 144, pp. 341–378, 2018.

[29] M. Becherif, H. Ramadan, K. Cabaret, F. Picard, N. Simoncini, and O. Béthoux, "Hydrogen energy storage: new techno-economic emergence solution analysis," *Energy Procedia*, vol. 74, pp. 371–380, 2015.

[30] M. Ilić, R. Jaddivada, and X. Miao, "Modeling and analysis methods for assessing stability of microgrids," *IFAC-PapersOnLine*, vol. 50, no. 1, pp. 5448–5455, 2017.

[31] M. Naderi, Y. Khayat, Q. Shafiee, and H. Bevrani, "Modeling of voltage source converters in microgrids using equivalent thevenin circuit," in *2018 9th Annual Power Electronics, Drives Systems and Technologies Conference (PEDSTC)*. IEEE, 2018, pp. 510–515.

[32] I. Sowa, T. T. Tran, T. Heins, D. Raisz, and A. Monti, "An average consensus algorithm for seamless synchronization of andronov-hopf oscillator based multi-bus microgrids," *IEEE Access*, vol. 9, pp. 90 441–90 454, 2021.

[33] T. T. Tran, I. Sowa, D. Raisz, and A. Monti, "An average consensus-based power-sharing among voc-based distributed generations in multi-bus islanded microgrids," *IET Generation, Transmission & Distribution*, vol. 15, no. 4, pp. 792–807, 2021.

[34] M. S. Thomas and A. Nisar, "Data-driven modeling and simulation of pv array," in *2015 2nd International Conference on Computing for Sustainable Global Development (INDIACom)*. IEEE, 2015, pp. 308–313.

[35] M. Tan and Z. Zhang, "Wind turbine modeling with data-driven methods and radially uniform designs," *IEEE Transactions on Industrial Informatics*, vol. 12, no. 3, pp. 1261–1269, 2016.

[36] U. K. Das, K. S. Tey, M. Seyedmahmoudian, S. Mekhilef, M. Y. I. Idris, W. Van Deventer, B. Horan, and A. Stojcevski, "Forecasting of photovoltaic power generation and model optimization: A review," pp. 912–928, jan 2018.

[37] Y. Wang and D. Infield, "Markov Chain Monte Carlo simulation of electric vehicle use for network integration studies," *International Journal of Electrical Power and Energy Systems*, vol. 99, pp. 85–94, jul 2018.

[38] R. C. Leou, J. H. Teng, H. J. Lu, B. R. Lan, H. T. Chen, T. Y. Hsieh, and C. L. Su, "Stochastic analysis of electric transportation charging impacts on power quality of distribution systems," *IET Generation, Transmission and Distribution*, vol. 12, no. 11, pp. 2725–2734, jun 2018.

[39] R. C. Leou, C. L. Su, and C. N. Lu, "Stochastic analyses of electric vehicle charging impacts on distribution network," *IEEE Transactions on Power Systems*, vol. 29, no. 3, pp. 1055–1063, 2014.

[40] E. Ghiani, A. Giordano, A. Nieddu, L. Rosetti, and F. Pilo, "Planning of a smart local energy community: The case of berchidda municipality (italy)," *Energies*, vol. 12, no. 24, p. 4629, 2019.

[41] B. Yan, M. Di Somma, G. Graditi, and P. B. Luh, "Markovian-based stochastic operation optimization of multiple distributed energy systems with renewables in a local energy community," *Electric Power Systems Research*, vol. 186, p. 106364, 2020.

[42] C. Orozco, S. Lilla, A. Borghetti, F. Napolitano, and F. Tossani, "An admm approach for day-ahead scheduling of a local energy community," in *2019 IEEE Milan PowerTech*. IEEE, 2019, pp. 1–6.

[43] S. Sen and V. Kumar, "Microgrid modelling: A comprehensive survey," *Annual Reviews in Control*, vol. 46, pp. 216–250, 2018.

[44] S. M. Zali and J. Milanovic, "Dynamic equivalent model of distribution network cell using prony analysis and nonlinear least square optimization," in *2009 IEEE Bucharest PowerTech*. IEEE, 2009, pp. 1–6.

[45] P. N. Papadopoulos, T. A. Papadopoulos, P. Crolla, A. J. Roscoe, G. K. Papagiannis, and G. M. Burt, "Measurement-based analysis of the dynamic performance of microgrids using system identification techniques," *IET Generation, Transmission & Distribution*, vol. 9, no. 1, pp. 90–103, 2015.

[46] M. Q. Tran, A. S. Zamzam, P. H. Nguyen, and G. Pemen, "Multi-area distribution system state estimation using decentralized physics-aware neural networks," *Energies*, vol. 14, no. 11, jun 2021.

[47] F. Ni, P. H. Nguyen, J. F. Cobben, H. E. Van den Brom, and D. Zhao, "Three-phase state estimation in the medium-voltage network with aggregated smart meter data," *International Journal of Electrical Power and Energy Systems*, vol. 98, pp. 463–473, jun 2018.

[48] D. S. Shafiullah, P. P. Vergara, A. N. Haque, P. H. Nguyen, and A. J. Pemen, "Gaussian Mixture Based Uncertainty Modeling to Optimize Energy Management of Heterogeneous Building Neighborhoods: A Case Study of a Dutch University Medical Campus," *Energy and Buildings*, vol. 224, oct 2020.

[49] W. Li, M. Rentemeister, J. Badeda, D. Jöst, D. Schulte, and D. U. Sauer, "Digital twin for battery systems: Cloud battery management system with online state-of-charge and state-of-health estimation," *Journal of Energy Storage*, vol. 30, aug 2020.

[50] S. Kaewunruen, P. Rungskunroch, and J. Welsh, "A digital-twin evaluation of net zero energy building for existing buildings," *Sustainability*, vol. 11, no. 1, p. 159, 2019.

[51] Q. T. Tran, Y. Besanger, M. Jung, T. L. Nguyen *et al.*, "Digital twin integrated power-hardware-in-the-loop for the assessment of distributed renewable energy resources," *Electrical Engineering*, pp. 1–12, 2021.

[52] W. Li, M. Rentemeister, J. Badeda, D. Jöst, D. Schulte, and D. U. Sauer, "Digital twin for battery systems: Cloud battery management system with online state-of-charge and state-of-health estimation," *Journal of energy storage*, vol. 30, p. 101557, 2020.

[53] H.-A. Park, G. Byeon, W. Son, H.-C. Jo, J. Kim, and S. Kim, "Digital twin for operation of microgrid: Optimal scheduling in virtual space of digital twin," *Energies*, vol. 13, no. 20, p. 5504, 2020.

[54] M. You, Q. Wang, H. Sun, I. Castro, and J. Jiang, "Digital twins based day-ahead integrated energy system scheduling under load and renewable energy uncertainties," *Applied Energy*, vol. 305, p. 117899, 2022.

[55] M. Uddin, M. F. Romlie, M. F. Abdullah, S. Abd Halim, T. C. Kwang *et al.*, "A review on peak load shaving strategies," *Renewable and Sustainable Energy Reviews*, vol. 82, pp. 3323–3332, 2018.

[56] H. Jiang, Y. Zhang, Y. Chen, C. Zhao, and J. Tan, "Power-traffic coordinated operation for bi-peak shaving and bi-ramp smoothing–a hierarchical data-driven approach," *Applied energy*, vol. 229, pp. 756–766, 2018.

[57] Y. Yang, H. Li, A. Aichhorn, J. Zheng, and M. Greenleaf, "Sizing strategy of distributed battery storage system with high penetration of photovoltaic for voltage regulation and peak load shaving," *IEEE Transactions on smart grid*, vol. 5, no. 2, pp. 982–991, 2013.

[58] M. Gottschalk, M. Uslar, and C. Delfs, "The smart grid architecture model–sgam," in *The Use Case and Smart Grid Architecture Model Approach*. Springer, 2017, pp. 41–61.

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