Recent advances on data-driven services for smart energy systems optimization and pro-active management

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***Abstract*— Optimization and proactive management of energy systems are crucial for achieving sustainability, efficiency and resilience in future smart energy networks. Data-driven approaches offer promising solutions for tackling the complex and dynamic challenges of energy systems, such as uncertainty, variability, and heterogeneity. Meanwhile, recent advances in decreasing hardware costs and improving data accessibility have allowed for the collection of high-quality data, leading to the development of more accurate and robust data-driven models of different energy systems. In this study, a comprehensive overview of current and future trends in data-driven optimization for smart energy systems is presented. After introducing the motivation and the background of this research field, the potential applications and benefits of optimization in various domains is discussed, such as electric vehicles charge, district heating networks and energy districts. Subsequently this review focuses on different methods and techniques for data-driven optimization and proactive management, ranging from scientific models to machine learning algorithms. Finally, the novel European project, DigiBUILD, is introduced, where different case studies are tested in several pilots, including electric vehicle charging management for increasing renewable energy source consumption, district heating network operative costs optimization and building energy and comfort management.**

Keywords—Fault Detection, Smart Building, Electric Vehicles, Energy Management, Optimization

I. Introduction

Urban areas in Europe are accounted for the 80% of energy use [1] and the combination of population increase and improvement in living standard ensure that energy demand is rapidly growing. Due to the unsustainability of fossil fuels and the intermittent nature of most of Renewable Energy Sources (RES), it is challenging to give balance and resilience of an energy system while aiming to its decarbonization. As a result, new approaches and paradigms are urgently needed to develop a sustainable energy system in the near future. The concept of Smart Energy Systems (SESs) was proposed to describe the expected new paradigm of energy systems by integrating multiple energy sources and vectors. These systems are considered "smart" because they include smart materials, devices and technologies [2] allowing for aligning consumption with RES generation and integrating different energy uses (i.e. electricity, heating and cooling). European Union support the research and the development of this concept by different initiatives [3] and digitalisation of energy sector is still necessary for achieving this goal [4].

In this framework, smart utility metering, Nearly Zero Energy Buildings, multi-source district cooling and heating systems, smart grids and RES, are all considered technologies to be very important for the development of future SES. Without holistically considering these aspects/systems by comprehensive solutions, the total performance of the systems is hardly optimized as their inherent interrelations among the systems are utilized. According to this, new control and optimisation approach are required for guaranteeing the best design and operation scenarios in such complex systems. Generally, the available literature offers different optimization purposes, using models and simulation environments it is possible to achieve the best design configuration (e.g., size, configuration presence of a component) or the best operation strategy according to input simulation data. Digital Twin (DT) technology, obtaining real-time simulation results basing on monitoring system, will allow facility managers (FMs) to obtain the best plan of action for managing the considered system.

Optimization tools are essential for improving the design and performance of energy systems such as District Heating Networks (DHNs). Future District Heating and Cooling systems will interact with different sources of heat or cool and will include also renewable energy producers which require new methods for heat unit cost estimation [5]. An optimal management will be also required to determine the most efficient combination of heat sources (e.g., power to heat, solar collectors and boiler) to meet the heating demand while minimizing costs and Green House Gas (GHG) emissions. In a study conducted by Reynolds et al. [6], a multi-vector energy center supplying a DHN was examined. By utilizing Artificial Neural Network (ANN) to forecast solar photovoltaic generation and building data (e.g., demand and interior temperatures), a Genetic Algorithm (GA) was employed to determine the optimal strategies for managing the DHN energy center. The results demonstrated a 44.88% increase in profit compared to the base case. In the work by Cox et al. [7], a similar data-driven approach was utilized. The authors successfully predicted and determined the optimal control strategy for an ice storage system in a District Cooling Network, with the aim of reducing operating costs while adapting to varying loads and energy prices.

Meanwhile, RES and building forecasting are essential components of the optimization services for the efficient management of energy resources and energy-efficient buildings, as accurate prediction of energy supply and demand can be critical for optimizing the use of RES and reducing energy waste. According to Sarmas et al. [8], deep learning techniques such as Long Short-Term Memory have been particularly effective in forecasting energy supply and demand. Moreover, it has been shown that incremental learning of such models can further increase forecasting accuracy by resulting in the construction of models that dynamically adapt to new patterns of streaming IoT data [9]. The use of such models enables energy managers can make more accurate predictions of energy supply and demand, allowing for more efficient allocation of energy resources. Thus, by optimizing energy consumption patterns and identifying areas of inefficiency, energy managers can reduce overall energy consumption, leading to reduced carbon emissions and cost savings, as well as to achieve optimal scheduling of flexible loads [10]. Using Data-Driven services it is possible to determine the optimal control of the power grid to minimize costs while ensuring a correct functioning. In this line, Pan et al. [11], developed a model for a microgrid consisting of an electrical storage system, a wind turbine, PV panels, and a building. By applying reinforcement learning techniques, the authors were able to devise medium-term and long-term scheduling plans to optimize yearly electricity costs, energy consumption by batteries, and energy generation from the wind turbine.

By the use of optimization methods, it is possible to determine the optimal charging schedule for EVs to minimize costs while ensuring that they are fully charged when needed. This can also help to enhance the use of renewable energy sources by aligning EV charging with periods of high renewable generation. Calise et al. presented an approach to optimize the charging strategy for a fleet of EVs within a DHN served by a cogeneration [12]. The implementation resulted in a primary energy saving index of approximately 32%, effectively reducing both primary energy consumption and carbon dioxide emissions within the investigated district. In [13] the authors presented an optimization method based on Multi-Agent Deep Reinforcement Learning. The simulations' results demonstrated that through optimal management of EVs and PVs, it is possible to reduce grid energy consumption by up to 40% compared to multi-home systems that do not engage in energy trading or EVs. Moreover, Liu et al. presented a study that highlights the advantages of employing a multi-objective optimal charging strategy for peak load shaving comparing different optimization algorithms [14]. By incorporating constraints such as load balance and capacity limits for EVs and electrical storage systems, their simulation results demonstrated a significant decrease in load fluctuation level (70.6%) and reduction in electricity cost (40.56%) compared to the base case.

Due to diffusion of smart sensors and smart buildings, the loads could be managed for achieving an increase in energy efficiency. Data-driven services could be used for real time and future fault detection in order to reduce yearly maintenance costs. Furthermore, there are a lot of examples of methods to determine the optimal operation of Heat Ventilation Hair Condition (HVAC) systems to minimize costs or emissions while ensuring that indoor comfort conditions are met. An indicative study is presented by Tsolkas et al. [15], where the authors present a novel model for enhancing thermal comfort in buildings using indoor temperature and humidity forecasts. Moreover, in a similar study, a Deep Neural Network (DNN) approach combined with a Particle Swarm Optimization (PSO) algorithm is used to maximize efficiency in HVAC systems in a commercial building with respect to temperature and humidity [16]. The authors demonstrated the effectiveness of DNNs in modelling the complex non-linear relationship between controllable settings and in reducing energy consumption by 7% during the study period. In the same line, Kusiak et al. [17] employed a combination of data-driven ANN forecasting models and a Strength-Multi-Objective PSO algorithm to compute various HVAC control strategies for office buildings. Due to the inherent nature of multi-objective analysis concerning both comfort and energy consumption, more than one solution was proposed. In a study conducted by Pezeshki et al. [18], a GA was utilized for the purpose of optimal design. The proposed model demonstrated superior performance in comparison to other existing approaches in the state of the art. Specifically, the model was able to determine the optimal placement of fan coils and radiators with the objective of minimizing both thermal discomfort and energy consumption.

In conclusion, this paper will explore current and future trends in data-driven approaches for optimization and management of future SESs. It will discuss various methods and applications of optimization in this field and present real-world example from the European project DigiBUILD. The paper will be divided into four sections: Section 1 will explore the reasons for research in optimization in SESs; Section 2 will focus on different methods of optimization and proactive management; Section 3 will present real applications of multi-purpose optimization in DigiBUILD project; and Section 4 will conclude the paper by summarizing key findings.

II. METHODS

This section presents different optimization methods to improve performance and resilience by reducing energy consumption, costs, and emissions, by detecting and predicting faults, and by optimizing design.

A. Energy, Costs and Emissions reduction

The increasing complexity of future energy networks, encompassing distributed heat source DHNs, smart grids, and prosumers, presents significant challenges in terms of management. In order to achieve decarbonization goals while simultaneously reducing costs, it is essential to implement optimal-pursuing algorithms. In this framework, according to [19], machine learning (ML) based on big-data collection is a promising solution for speeding up the process of optimum research and for increasing efficiency in DHNs. In general, the search for optimal solutions involves finding the minimum or maximum value of an objective function (or multiple objective functions in the case of multi-objective optimization). In the context of energy, this function is typically related to the minimization of costs, energy consumption, or emissions. The objective function represents the final step of the optimization problem, which is subject to various constraints that limit the solution space [20]. Due to variety of optimization algorithms and approaches available, many of which are reported in [21], it is important to provide examples of their use for achieving energy efficiency improvement in order to guide the selection of the most suitable alternative.

GAs are one of the most used algorithms in energy efficiency application. This algorithm is based on the principles of natural selection and genetics: using a population of potential solutions to a problem and applying genetic operators (such as selection, crossover, and mutation) the population of solution will improve itself (evolving) over time. In the study presented by Akhlaghi et al. [22], the optimization process requires a multi-objective evolutionary optimization using GAs and forecasts from a feed-forward neural network. This method was applied to a dew point cooler showing COP and power consumption improvements. Arabali et al. [23] propose a comparison between GA and discontinuous nonlinear programming optimization for optimally balance building HVAC load, energy storage, PV and wind turbine production. Describing constraints and objective function details, their method was able to provide in different scenarios cost reductions and efficiency improvements.

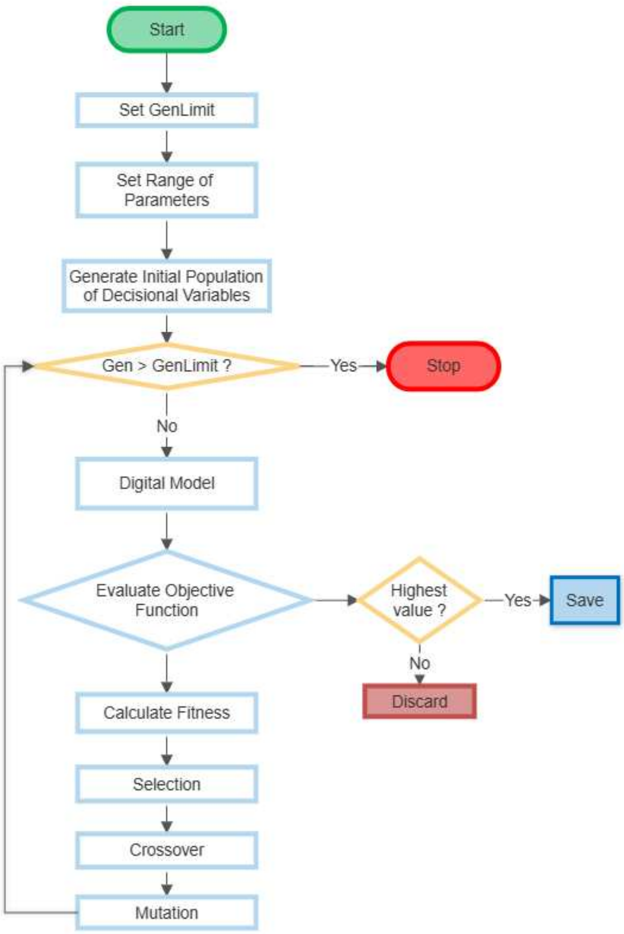

Fig. 1. Simplified flowchart of a Genetic Algorithm optimization

B. Design

Design optimization involves determining the best configuration of different components of an energy system to minimize costs while ensuring that performance requirements are met. This can involve selecting the size and location of different components, as well as determining their interconnections. Zeng et al. conducted a study on optimizing the pipe diameter of a district cooling network using a GA [24]. After developing a mathematical model of the district and formulating the optimization problem, the results, based on hourly data, revealed the optimal pipe configuration. The study also demonstrated that using distributed variable speed pumps could reduce yearly costs by up to 27.7% compared to the base case. The novel approach proposed by Saikia et al. simplifies the selection of building retrofit options and it was tested in a real case study [25]. By utilizing an improved GA and spatial discretization of the structural layer, the authors demonstrated that the solution proposed by their method resulted in a reduction of electricity consumption by 9.2 kWh/day in the real building. In [26], a comprehensive methodology for determining the optimal design and operation strategy for a polygeneration system serving a cluster of buildings is presented. The methodology takes into account the size and presence of each component, such as cogeneration units, thermal energy storage, absorption chillers, and pipes. The authors detail the constraints, objective functions, and decisional variables of their optimization algorithm for both individual buildings and the entire cluster. Results presented in [27] demonstrate the capability of the developed mixed integer linear programming algorithm to determine the optimal size under varying initial conditions (e.g., as location and energy prices) as well as the optimal operation for managing the load of individual power units and thermal flows between buildings.

C. Fault detection

In addition to optimization methods, fault detection and predictive maintenance are also important aspects of SES monitoring. In this framework, using only measured and monitoring data, data-driven approaches are widely used in modelling real systems and in detecting present and future faults. In a study by Kim et al. [28], ML methods were compared for their effectiveness in detecting faults in DHNs. The proposed model, based on a Gradient Boosting Regressor, was able to predict the operational behaviour of a DHN substation by distinguishing between well-performing and faulty substations. The algorithm was trained using data from a Swedish DH system proving high accuracy. Hosamo et al. [29] presented a study where, using monitored occupants' comfort data (thermal, visual, and acoustic), they proposed different algorithms (e.g., Bayesian Networks, AHU performance assessment rules, etc.) for detecting accurately faulty systems in existing Norwegian buildings. By using advanced sensors and monitoring techniques, it is possible to detect faults or anomalies in order to take corrective action before they cause serious problems. Rizeakos et al. present a study that introduces a data-driven algorithm for fault location identification and type classification in low voltage distribution grids [30]. By utilizing synthetic data and employing a convolutional neural network to identify and locate faults, the algorithm achieved an accuracy of over 91% in detecting faults and identifying the correct branch. The authors also used Bayesian Optimization to calculate the optimal hyperparameters for their model.

III. DigiBUILD Services

The DigiBUILD European project aims to apply optimization and efficient management methods to SESs. Innovative data-driven services will be developed for the management of building and DHNs. These optimization services will target cost and energy consumption reduction across multiple cutting-edge areas within the current scientific and research landscape. This will be achieved through the practical application of pilot projects. Algorithms will be employed to provide suggestions and alerts for anomalies in building systems as part of fault detection and proactive management services. The interaction between EVs and RES both locally and within the national grid, will be optimized through the development of efficient management methods. Additionally, two DHNs will benefit from optimal management services that efficiently utilize various heat sources (e.g., biomass and gas boilers, photovoltaic-to-heat technologies) to reduce operational costs.

A. *Services for fault detection and proactive management*

These applications aim to detect faulty sensors and provide maintenance and operation suggestions related to energy consumption and discomfort in buildings of the University College of London and Iasi (Romania).

Data is stored in 15-minute intervals from different sensors designed to track variables needed for the estimation of indoor and outdoor air quality, building thermal and electric consumption, and occupancy levels. Upon analysis of the collected data, rule-based algorithms will be utilized to identify issues such as sensor malfunctions (by verifying the validity of each measurement) or improper functioning of HVAC systems that may cause discomfort (by comparing measured variables with comfort or set-point conditions). Concurrently, AI algorithms will be employed to forecast building load consumption at various levels of detail (e.g., room, system, or building). These predictions will be compared with real-time measurements to detect anomalous energy demand in specific rooms or buildings. In the event of sensor issues or unexpected energy demands, the cause will be investigated using data-driven algorithms. Within this framework, ML algorithms will be trained on various types of data (e.g., electric and thermal consumption, air temperature, water consumption) to develop real-time and future fault detection algorithms supported by future forecasts. Based on these results, the building manager will receive reports of malfunctions and recommendations for resolving problems in the buildings and optimizing in real time HVAC system operation and maintenance.

B. *Services for Balancing PV production with EVs and building loads*

One application of these services is to balance PV energy with EV charging and building loads to maximize self-consumption while reducing operational costs and associated GHG emissions. In a case study involving Emotion, an Italian company, multi-purpose algorithms will be used to match PV production with the charging of a fleet of EVs.

Vehicle data will be collected using on-board diagnostics (OBD) systems, while smart meters installed in the buildings and charging columns will gather data on electricity consumption. An optimization algorithm will consider various decision variables (e.g., charging power, number of vehicles to charge, time scheduling), user vehicle needs, real-time and forecasted data of PVs and building load to suggest a charging schedule and modulation strategy. The DT of the user will then autonomously charge the vehicles based on the optimization results. Building modulable loads (e.g. machines or electric boilers) will also be taken into account: if further energy savings are possible, another algorithm will be employed. A decision support system will advise the FM on how to manage building loads to increase consumption of available PV production. The optimization algorithms will also run in real-time to make automated corrections based on monitored perturbations.

These methods will help the pilot achieve several goals. Firstly, electricity consumption from the grid will be reduced, lowering costs and GHG-related emissions. Optimal management will also reduce peak power consumption, further reducing billing costs. Once these services are implemented and results are collected, they will serve as a beacon for future applications of these algorithms in building and EV management to move closer to zero emissions goals.

C. *Services for EV's Management for CO_2 reduction*

This use case proposes an optimization algorithm that leverages available data from grid operators, building data, and e-mobility data to determine optimal EV charging schedules. E-mobility is a very important part of the flexible sources and thus several research attempts focus on optimizing its operation [31]. In this context, grid operator provides pertinent information on the CO_2 footprint of the energy to be consumed, through energy mix and grid status data, whereas building data includes historical consumption data and pricing policies. E-mobility data, on the other hand, captures EV historical data from charging sessions and electric vehicles. The proposed optimization algorithm employs machine learning-based forecasts to combine the above variables and ensure that EV charging needs are adequately met. The optimization process also maximizes the use of green energy from the grid while minimizing costs. Furthermore, the algorithm ensures that the total building consumption remains within acceptable limits during peak times. For the needs of this service either a global optimization algorithm or a heuristic algorithm may be used according to the computational complexity of each specific use case [32].

The main objective of the algorithm is to provide optimal EV charging schedules that meet charging requirements, avoid straining the total building consumption and, above all, maximize the use of green energy, i.e. energy generated by renewable energy sources and not instead of combustion processes. The algorithm's output comprises EV charging schedules and a report that compares recommended behavior with actual actions taken. The report includes detailed information on the followed charging schedules and the carbon footprint achieved. By examining this data, it is possible to evaluate the effectiveness of the algorithm in providing optimal charging schedules and identify areas for further optimizing energy usage.

The findings of this use case will have significant implications for imposing better energy management and sustainability practices. By optimizing EV charging schedules, energy consumption and costs can be reduced, and carbon emissions can be minimized. The algorithm's ability to compare recommended behavior with actual actions taken provides valuable insights into user behavior and how it affects energy usage and carbon footprint, thus this knowledge can be used to develop policies that encourage sustainable behavior and optimize energy use in buildings.

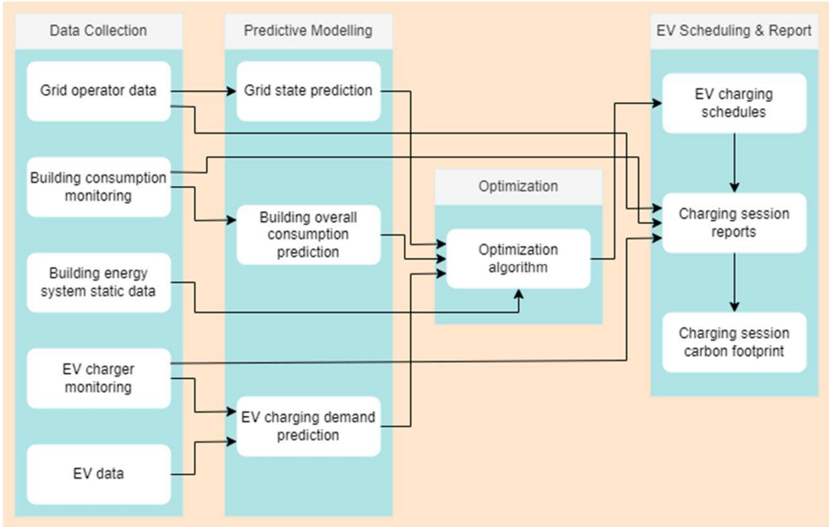

Fig. 2. Flowchart of service for EV's Management for CO_2 reduction

D. *Services for optimal management in DHNs*

DHNs provide an efficient and sustainable means of distributing heat to multiple buildings within a community. However, optimizing heat production within a DHN can be challenging due to the complex interactions between heat sources, distribution networks, and building loads. In this context, DigiBUILD will offer algorithms to VEOLIA's DHNs to optimize heat production, taking into account these complexities to improve efficiency and reduce costs for district residents.

CP Fasa and CP Rio Vena are two distinct DHNs that require optimization. CP Rio Vena produces heat using three different gas boilers and supplies residential buildings. CP Fasa is a 4th Generation DHN with multiple heat sources, including a 3.7 MW gas boiler, two 540 kW biomass boilers, and an electric boiler that uses PV production. By collecting multiple data, including heating and domestic hot water demand for each building, weather conditions and PV production, a ML forecasting model could be trained. In CP Fasa, based on prevision of PV production and building heating loads, and boiler efficiency, the algorithm will suggest the optimal management strategy. At CP Rio Vena, the DHN operation will be guided through the use of an algorithm that takes into account the forecasted heating demand and a data-driven model for calculating boiler efficiency. A digital model of each DHN will be simulated by the optimization algorithms, varying different decision variables (e.g., boiler load level, supply temperature, flow rate etc.) to minimize the costs. The DT of the DHN will also include the same model and optimization algorithms to allow the manager to hypothesize and test different operational scenarios.

By utilizing these services, the FM will be able to determine the best strategy for reducing primary energy consumption and costs on district heating while also increasing overall system efficiency and moving towards decarbonizing the urban sector.

IV. Conclusions

The optimization of SESs is a critical component in achieving the EU decarbonization objectives. Utilizing data-driven algorithms can decrease energy consumption, enhance energy efficiency, and demonstrate the advantages of digitalization within energy systems. This paper provides a comprehensive review of the diverse applications of optimization algorithms within systems, including buildings, micro grids and DHNs. This review also proposed different data-driven algorithms examples which have been classified based on their application in efficiency improvement, optimal design, and fault detection. While there is a wide range of optimization algorithms available, the GA seems to be up to date the most prevalent.

Future applications in the framework of DigiBUILD European project were hereby introduced. These applications include services for fault detection and proactive management and services for the management of EVs and building loads to reduce emissions and energy costs. Finally, we presented DHN management services for reducing heat supply costs by optimal heat source management including RES and gas boilers.

In conclusion, in this work it has been proved that optimizing future SESs is essential for achieving the EU goals towards the zero-emissions objectives. Data-driven algorithms are a necessary medium due to increasing of complexity of the energy sector and its management. The applications within these systems are diverse and various algorithms are available in scientific literature with the scope of reducing operating costs, energy consumptions and increasing revenue.

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