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TOPICAL REVIEW

A Review on the Applications of PSO-Based Algorithm in Demand Side Management: Challenges and Opportunities

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ABSTRACT The increase in energy consumption, environmental pollution issues, and low-carbon agenda has grown the research area of demand side management (DSM). DSM programs provide feasible solutions and significantly enhance the efficiency and sustainability of electrical distribution systems. This paper classifies and discusses the broad definition of DSM based on the comprehensive literature study considering demand response and energy efficiency. The implementation of Artificial Intelligence algorithms in DSM applications has been employed in many studies to help researchers make optimal decisions and achieve predictions by analyzing the massive amount of historical data. Owing to its simplicity and consistent performance in fast convergence time, Particle Swarm Optimization (PSO) is widely used as a part of the swarm AI algorithm and has become a prominent technique in the optimization process to exploit the full benefit of the demand-side program. The variants of PSO have been developed to overcome the limitations of the original PSO and solve the high complexity and uncertainty in the DSM optimization process. The proposed PSO-based algorithm can optimize consumers' consumption curves, reducing the peak demand and hence minimizing the electricity cost when integrated with the DR programs or EE measures. The research works of the PSO algorithm in DSM have seen an increasing trend in the past decade. Therefore, this paper reviewed the application of the PSO-based algorithm in DSM fields with some constraints and discussed the challenges from the previous work. The potential for new opportunities is identified so that PSO methods can be developed for future research.

INDEX TERMS Demand side management (DSM), demand response (DR), energy efficiency (EE), meta-heuristic algorithms, particle swarm optimization (PSO), swarm intelligence.

I. INTRODUCTION

The increasing crisis of global warming has made it more challenging for the world to move toward a climate-resilient, low-carbon, and sustainable future in the 21st century. Burning fossil fuels and deforestation are two outcomes of human activity that have contributed to the rise in CO_2 emissions [1]. CO_2, the dominant greenhouse gas (GHG), has become a major global concern due to climate change. Based on the assessment report by Intergovernmental Panel on Climate Change (IPCC), the global net anthropogenic GHG emissions in 2019 have increased by about 6.5 $GtCO_2$-eq compared to 2010. This increase directly came from the energy supply (34%), industry (24%), agriculture, forestry, and other land use (22%), transport (15%), and buildings (6%) sectors [2]. Scientifically, the average global temperature on Earth is closely related to the concentration of GHGs in the earth's atmosphere. Global warming caused by human activities is predicted to have increased by 1.0°C above pre-industrial levels, and if it remains to rise at the current rate, it will

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probably hit 1.5°C between 2030 and 2052 [3]. The charts in the global climate effort, including United Nation Framework Convention on Climate Change (UNFCCC), Kyoto Protocol, and Paris Agreement have reached a target to combat climate change by limiting the global average temperature to 1.5°C above pre-industrial levels by reducing CO_2 emission substantially before 2030 [4]. However, national pledges are not enough to overcome this climate issue alone. These targets would necessitate swift, extensive, and significant systemic changes, including a variety of technologies and behavioral improvements, investments in clean energy sources, and energy efficiency increases of five times by 2050 [5]. Accordingly, reducing human-caused emissions to as close to zero as possible to reach the Net-Zero emissions target around mid-century [6]. Enhancing energy efficiency and lowering energy demand are widely recognized as the quickest, safest, and cheapest ways to combat climate change [7].

In recent years, Demand Side Management (DSM) has been one of the approaches to optimize energy efficiency in electricity distribution. DSM is the practice of planning, installation, and monitoring by the electricity utility that can impact energy use by changing the consumption patterns of consumers to achieve the necessary changes in load shape. DSM aims to flatten the load profile by encouraging consumers to reduce the demand in peak hours or transfer the demand from peak to off-peak hours and preferably follow the generation pattern [8]. The main categories for DSM activities are demand response (DR) and energy efficiency (EE), as shown in Fig. 1. The demand-side solutions provide maximum benefits and are integrated with lesser risk compared to supply-side options [8], as they are potentially improving the network load pattern [9], lowering air pollution [10], reducing emission [11] and healthcare cost [12] due to its positive environmental impact. Therefore, the sustainable energy transition required a momentous effort from various scales, such as government, industry, and academia. The bright potential of DSM in industries due to the high power consumption of individuals, which encourages and facilitates involvement in DSM activities, low cost is needed because the infrastructure for metering is already in place and industrial processes are conducted in isolated locations, resulting in minimum effort for occupant comfort [13]. In line with Industrial Revolution 4.0, DSM plays a significant role in attaining efficient energy generation and utilization, particularly for transitioning business operations toward smart factories [14].

In the research area, significant references focus on the concept of DSM. A comprehensive review of the DSM, which explained the basic idea, main subjects, and practical methods by evaluating the DSM's theoretical foundation has been overviewed in [15]. The detailed issue of DSM has been emphasized in a few studies, such as demand response [16], [17], price-based program on DR concept [18], microgrid [19], energy efficiency [20], and its co-benefits [21]. Reference [22] presented the design of

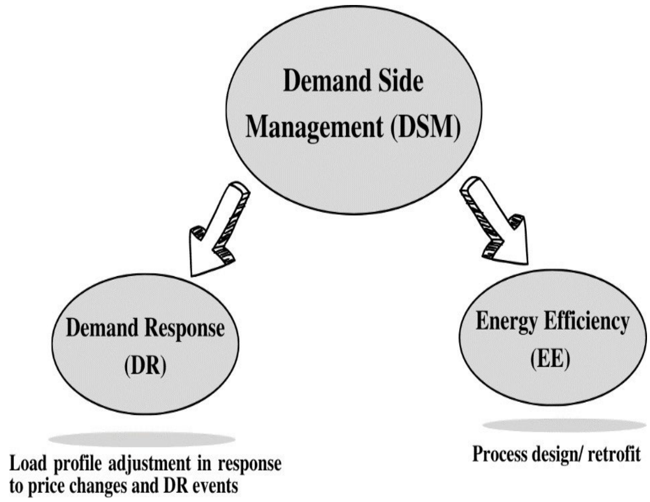

FIGURE 1. **Categories for DSM activities. EE is the measure to be taken by consumers, while DR is the program introduced by the utility.**

DR programs and policy in European states, while strategies to accelerate the UK consumer's participation in DR have been discussed in [23] with the implementation of technologies. Furthermore, the application of DSM integrates with renewable energy [24], storage systems [25], electric vehicles (EV) [26], and building energy management systems (BEMS) [27] has been widely adopted to promote a sustainable environment and reduce environmental pollution.

The growing innovation of Internet-of-Things (IoT) monitoring, advanced metering infrastructure (AMI), automation technologies, and distributed energy resources have encouraged entities of the energy demand side to be active prosumers (producers and consumers) in the operation of the electrical grid rather than passive energy consumers. Moreover, these data acquisition technologies associated with the advancement of artificial intelligence (AI) can potentially widen the opportunities for researchers to combine interdisciplinary knowledge, examine energy consumers' operational environment in further detail, and formulate new data-driven demand-side management strategies. The appliance level energy characteristic (ALEC) can be utilized to monitor the usage of electricity appliances and energy consumption behavior closely, thus assisting the utilities and stakeholders in implementing practical DSM activities for the residential or other sectors through intrusive load monitoring (ILM) or non-ILM (NILM) techniques as discussed in [28]. Further, AI approaches forecast power demand and generation and provide better stability and efficiency for power systems [29]. On the other hand, evidence shows that developments of AI could enhance the knowledge of climate change and the modelling of its potential effects, particularly when it comes to achieving Sustainable Development Goal (SDG) number 13 on climate action. In addition, AI will also promote low-carbon energy systems with the integration of energy efficiency and renewable energy necessary to combat climate change [30]. For instance, the various industrial sector in China could obtain the optimal path for energy efficiency enhancement which could reduce CO_2 emission by 58.31% through the prediction of the AI algorithm model [31].

Metaheuristics algorithms (MA) are a prevalent part of AI for solving optimization problems. These techniques have an acceptable performance to solve any optimization problems by finding a near-optimal solution with a limited computation burden [32]. Moreover, they are more efficient and converging than the classical approaches because of their efficiency in exploring the search space to reach a global optimum solution [33]. MA can be applied in problems with a large number of decision variables and easily adopted to a problem that has several constraints [34], such as real-world engineering design problems [35], [36]. MA optimization techniques are currently used to overcome the limitations of mathematical optimization with some great features such as fine-tuning to improve their performance, fast computing time, efficient exploration and exploitation due to nature-inspired approaches, and the independent nature of the objective function. As a result, they are effective methods for resolving optimization challenges [37], [38]. The newly formed MA methods have been very beneficial to the engineering field. Many issues, including multi-objective optimization issues as well as continuous, discrete, constrained, and other challenges, have been resolved using them. As a result of their extensive use, new scientific subfields have arisen [39]. Some of the most prominent MA found in the literature are Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Genetic Algorithm (GA) and Differential Evolution (DE).

Numerous models have been developed with MA in the DSM optimization field. For instance, ACO based method has been proposed to optimize the residential load profile with DSM techniques while analyzing the impact of DR tariff on the user's electricity bill [40], [41]. The DE with toroidal correction has been utilized to achieve a good convergence of the algorithm and reduce the possibility of stagnation in local optima in solving the industrial load optimization considering the energy and labour costs [42]. The GA is adopted in [43] to minimize the cost and maximize the load factor simultaneously for DR residential. The newly introduced MA, namely the virulence optimization algorithm (VOA) and earthworm optimization algorithm (EWOA) are utilized individually in solving the microgrid scheduling optimization problem, which effectively shifts the energy consumption from peak to off-peak hours. As a result, the proposed method is able to minimize the mismatch between total generation and demand and the overall electricity bill [44]. Meanwhile, Grey Wolf Algorithm (GWA) shows high efficiency in solving a complex problem in energy management strategies considering hydrogen storage systems and multiple renewable sources to reduce its final operating cost [45]. The integration of DR with distributed generation in managing the transmission congestion deduced the overall cost, CO_2 emission, and maximum line loading using the Multi-Objective Salp Swarm Algorithm (MOSSA) [46].

For effective scheduling of intelligent home appliances in the energy management system, the Dragon Fly Algorithm (DA) [47], ACO [48], a hybrid of the Harmony Search Algorithm and GWA (HGWA) [49], and a hybrid of Bird Swarm Optimization and Cuckoo Search Optimization (HBCO) [50] are proposed for minimizing the consumer electricity bill, peak to average ratio and waiting time. The dynamic pricing scheme schedules the appliances in off-peak times while considering user comfort. Despite their great performance in solving complex problems, there is no ideal algorithm to deal with any kind of problem, as stated in the No-Free Lunch Theorem by Wolpert and Macready, due to rises concern about the nature of these algorithms that are not adequately mathematics-based, and the convergence is not guaranteed [51]. Recently, the variant of a well-known approach in MA, Particle Swarm Optimization (PSO), has been widely developed to improve its performance. The fact that it can be utilized directly in continuous real number space is one of its advantages. Also, it does not use the gradient of objective function like others. It looks to be a straightforward technique that efficiently optimizes several different functions. Although the PSO was first developed to address unconstrained problems, it has now been used to address constrained problems by utilizing several distinct strategies [50]. Thus, this study aims to overview the PSO-based algorithm in solving the constrained problems in the DSM applications.

The literature survey indicates plenty of review studies on the optimization of DSM. References [52] and [53] has reviewed the application of AI in the energy management system to improve energy efficiency in a smart building. A comprehensive overview of optimizing and controlling the energy system for DR applications in the smart grid, such as smart appliances, EVs, batteries, heating ventilation air-conditioning (HVAC) by using reinforcement learning (RL; an agent-based AI algorithm) is presented in [54]. An interesting review in [55] discussed the application of AI in DSM techniques while analyzing its objective function and constraints. However, the limitation of the work only focuses on the residential sector. Scholars in [56] and [57] presented a review on the optimization of DSM in district heating with a few similar goals: profit, renewables deployment, and operation cost. On the other hand, [58] provided a review of the MA based on the energy management system according to different objectives (forecasting, demand management, economic dispatch (ED), and unit commitment). The authors conclude that MA like PSO and machine learning approaches are suitable for forecasting and ED-based application. Moreover, the variety of PSO models for residential load scheduling considering DR has been discussed in [59]. A detailed review of each study is presented in Table 1.

The studies demonstrate that AI modelling in the applications of DSM is a developing research area with opportunities for further review, as each scholar emphasizes the subject

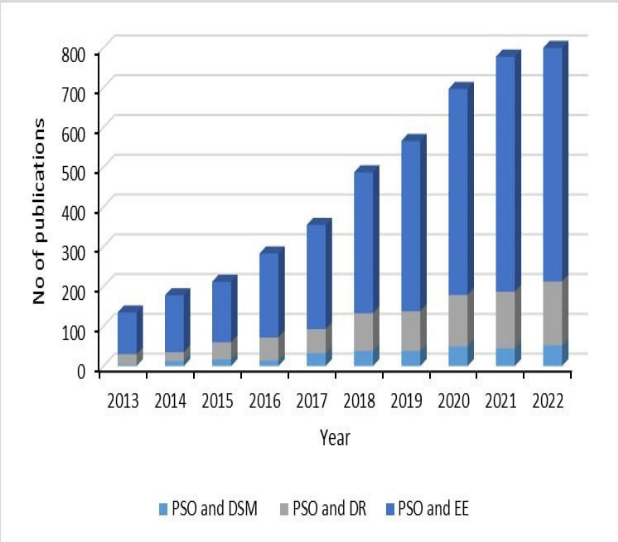

FIGURE 2. Number of publications with respect to years.

differently. While exploring the DSM optimization techniques, we noticed that no study had gathered the research conducted on applying PSO-based models in the DSM and its subfields, such as demand response and energy efficiency. Thus, the authors believe a review within this field could address this research gap and and not duplicate existing work to benefit future researchers. On the other hand, PSO contributes more to swarm intelligence literature than any other SI-based technique in the past years, indicating the significance of PSO and its easiness and practicability in various fields of application [60]. Thus, the PSO models are chosen to support the review work in the DSM application since the abundance availability of research studies related are published in the search engine such as SCOPUS when the following queries are used, which are found in the title, abstract, or keywords.

- Particle AND Swarm AND Optimization AND Demand AND Response
- Particle AND Swarm AND Optimization AND Energy AND Efficiency
- Particle AND Swarm AND Optimization AND Demand AND Side AND Management

Fig 2 depicts the number of publications according to the queries used with respect to years. During these ten years, the research of PSO-based algorithms in DSM applications is rising and become more dominant in the EE than DR programs. Based on this background, this paper aims to systematically review the literature on PSO-based algorithm applications, covering several challenges and opportunities in demand-side management. The contributions of this review paper can be summarized as follows:

- It provides an overview of the theory and implementations of DSM activities considering DR and EE programs
- The application of the PSO-based methods is specifically reviewed in different categories of DSM for different objective functions considering the practical constraints
- It discusses challenges and potential opportunities for investigation of future research areas in the modelling and optimization of DSM

The structure of this paper is organized as follows. Section II presents the overview of PSO. Section III reviews research works on PSO-based algorithm applications in demand response. Section IV emphasizes an overview of PSO-based algorithm application in energy efficiency. Section V discusses the challenge and limitations of the PSO models in the DSM field based on the previous works. Section VI outlines the suggestion for the future direction of research works, and Section VII summarizes the main findings of this paper as a conclusion.

II. OVERVIEW OF PARTICLE SWARM OPTIMIZATION (PSO)

Designing novel computational approaches are usually inspired by a natural and biological system. In the context of MA, natured-inspired algorithms have been utilized for searching and planning, such as finding the sequences of actions required to reach the agent's goals [61]. In particular, swarm intelligence (SI) is a subset of MA featuring the intelligent behavior of biological swarms by the individual's interaction in this environment to solve real-world engineering problems through the simulation of such biological behavior [62]. The Particle Swarm Optimization (PSO) algorithm, which is the major branch of swarm intelligence, is based on the random-search optimization technique [63] and was inspired by social behavior observed in nature, such as schools of fish, a swarm of bees, flocks of birds, and even human social behavior [64]. Each particle in the search space refers to the candidate solution, whereas the food sources represent the global optimum of the problem. The best experience obtained by each PSO particle is called personal best (pBest), and the entire population, known as global best (gBest) throughout the optimization process can be used to modify the search trajectory for that particle. The updated velocity and its position are presented in (1) and (2) respectively.

$$V_{ij}^{t+1} = \omega v_{ij}^{t} + c_1 r_1 (p_{best,ij}^{t} - x_{ij}^{t}) + c_2 r_2 (g_{best,ij}^{t}) \quad (1)$$

$$x_{ij}^{t+1} = x_{ij}^{t} + v_{ij}^{t+1} \quad (2)$$

where t is the repetition number of the algorithm, ω denotes the inertia weight of each agent, v shows the speed of the agent at t (at the i-th row and j-th column), x^t is the position of the agent at t (at the i-th row and j-th column), c_1 and c_2 are the learning factors of the algorithm, r_1 and r_2 denote the accidental numbers, p_{best} is the optimal fitness of each particle and g_{best} is the global of each agent [65]. PSO has been effectively used to resolve a variety of real-world optimization issues because of its simple implementation and promising convergence feature [66], [67], [68], [69]. Since

PSO is guided by two mathematical equations which direct the particles to the optimal point, it is much faster than the other heuristic optimization techniques [70]. A few advantages and disadvantages must be considered when applying PSO, as summarized below [71], [72].

Advantages:

- Good memory capability
  - Strong robustness and quick convergence to optimization
- Has only a few parameters to adjust
- Easier to implement and hybridize with other

algorithms

- Computational ability is less influenced by the initial solutions
- Flexibility in modifying its operators
- Suitable for optimizing a global search

Disadvantages:

- Easy to trap in the local optima
- Premature convergence
- Challenging to deal with discrete variables

Numerous works of hybrid and modified versions based on PSO have been introduced since its advent in 1995 to improve the convergence speed and prevent premature convergence [72], [73], [74]. Generally, research on the development of PSO can be classified into three categories: hybrid versions, topological structure, and parameter selection [75]. Table 2 illustrates some of the well-known PSO variants which have been used in past research. However, researchers have shown that PSO variants may have different performances level when solving different problems, thus, it is necessary to find suitable PSO variants for different problems at different stages to efficiently solve the optimization problem [76]. According to the modern intelligent optimization theory, it is essential for an optimization algorithm to keep a balance between exploration and exploitation, an excessive emphasis on one of them will adversely influence another [77]. Thus, the variants of PSO are proposed to strike a balance between exploration and exploitation and overcome the limitations of the conventional PSO.

III. CLASSIFICATION OF DEMAND RESPONSE PROGRAM

DR can be interpreted as the responsive actions by the end-users from their usual consumption pattern to the changes in the electricity price over time or to incentive payments designed to mitigate electricity consumption use when wholesale market prices are high or when the reliability of the system is jeopardized [89]. In other words, DR is the reduction of hourly power consumption in response to high electricity prices [90]. It is noteworthy that involvement in these programs causes the load consumption to be shifted from peak hours to off-peak hours, thus improving the system's adaptability, stability, and dependability [91]. The primary objectives of the DR program include minimizing the total power consumption, reducing the total power generation needed, adjusting demand to match supply availability, and reducing or even eliminating the overloads in the distribution system [92]. Thereby, the issues of peak generation and demand mismatch, peak regulating capacity, and a lack of reserved capacity can be resolved [93].

The research efforts on DR programs can be presented into three methodologies; 1) the control mechanism of the DR procedure, 2) the motivations offered to customers to reduce or shift their consumption, and 3) the DR decision variable [94]. In this sub-section, the discussion is focused on the motivation method offered to consumers for load shifting and lower energy consumption as the initiatives. Fig. 3 illustrates the prominent classes to adjust the electricity load in this method which are the incentive-based DR programs and price-based DR programs. In the incentive-based, the utility incentivizes the consumers to follow the electricity consumption guided from the supply side, meanwhile, in the price-based, the different rates are charged to consumers depending on a certain period, thereby the retail electricity tariff is influenced by the electricity supply cost [92]. The former class is more suitable for the industrial sector, while the price-based is more suitable for the residential sector [95]. Cost-sensitive consumers engaged in the DR programs by modifying energy consumption in response to time-varying prices. The demand response program offered by the utility is crucial to avoid potential system problems such as power imbalances, voltage fluctuations, and blackouts, as well as to save money on capital expenses related to investing in greater generation capacity to satisfy peak load demand [96]. Therefore, a vital need for consumer involvement in the DR program to maintain the supply-demand balance.

A. PRICE BASED-PROGRAM

In this type of DR, the consumers volunteer to adjust their consumption pattern based on the electricity tariffs designed by the utility since the energy cost dynamically varies with time. Time-varying tariffs may be used to utilize the variations in energy prices on the wholesale market directly to customers, causing them to pay for the electricity cost at different hours of the day as opposed to time-invariant tariffs [97]. The pricing scheme under this program is discussed as follows:

1) TIME OF USE (ToU)

TOU tariff aims to modify consumers' daily electricity use patterns. In general, TOU will encourage users to minimize electricity consumption in peak periods and shift it to off-peak periods by adjusting or modifying their electricity usage. In this way, consumers can mitigate the price of their electricity bills by consuming more during the low price and reducing during the high price. Thus, consumers can continue to consume the same amount of electricity while paying a lower electric bill [98]. There are two types of TOU pricing which are static TOU (sTOU) and dynamic TOU (dTOU). The prices in sTOU change by time of day between predetermined price levels and throughout certain time intervals. Seasonal differences may apply. Contrarily, in dTOU, prices

TABLE 1. Comparison analysis of related literature reviews for different review targets of DSM.

Ref	Optimization techniques			DSM aspects			Contributions
	PSO	RL	AI	DR	EE	DH	
[52]			✓		✓		This study grouped the research works on BEMS according to the concept of "Autonomous Cycles of Data Analysis Tasks" while discussing the current challenges and opportunities for each domain.
[53]			✓	✓	✓		This study presents the fundamental of a cyber-physical system in a smart building, the role of AI-based approaches in DR and BMS, and summarized the challenges and opportunities for implementation of AI-based applications for smart building
[54]		✓		✓			This study highlighted the interdependence of DR programs, and modelling techniques of various versions of RL as well as the potential control architecture in diverse energy systems considering DG at the building
[55]			✓	✓	✓		This study explored various optimization models, technology, infrastructure, communication, and control protocols in RDSM while identifying the challenges in its implementation and future scope
[56]			✓			✓	This study presents the terminology and the stages for DSM implementation in DH while analyzing the related research works including simulation and real application in terms of goal, intelligence model, influential parameters in building indoor conditions, regulation method, and results.
[57]			✓			✓	This study presents the different types of optimization problems, constraints, and techniques in addition to optimization tools used in the district energy system to solve the different district-level problems considering the cooling and heating thermal network
[58]			✓		✓		This study presents the research works on AI-based EMS based on five major groups in microgrids while identifying the related problems in forecasting, demand management, economic dispatch, and unit commitment as well as future recommendations
[59]	✓			✓			This study evaluated the different PSO methods considering the optimization objectives, constraints, and applications in energy resources such as distributed generation, household devices, heating/cooling devices, energy storage, EVs, and power transformers. The evaluation is based on system design, accuracy, and complexity and discussed in future research.
Proposed work	✓			✓	✓		This study presents a brief overview of DSM implementation while focusing on the different applications of PSO-based algorithms. This study also discusses the challenges and potential opportunities for investigation of future research areas in the modeling and optimization of DSM.

change between predetermined price levels, but the timing is not regulated [99]. For example, in Malaysia, a static pricing scheme is adopted for commercial and industrial consumers who are charged based on two periods of peak and off-peak for TOU tariff and the addition of a mid-peak period for a new tariff, Enhanced TOU (ETOU) within a compatible

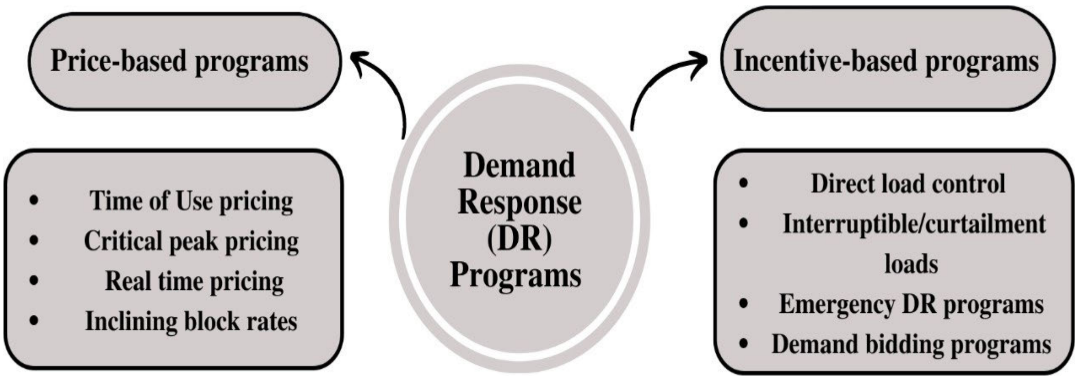

FIGURE 3. Classification of the DR program.

rate [100]. Policymakers have considered TOU pricing as the feasible DSM option, particularly in regions where smart metering technology adoption has reached (or will reach) double-digit prevalence in the near years. TOU pricing does not need a complicated two-way communication system in terms of smart metering device functionality. This simplifies communication technology used in smart meters as well as data administration for the supplier [101].

2) CRITICAL PEAK PRICING (CPP)

The CPP tariff is an example of an event-based program. A higher rate of energy consumption is charged when critical peaks happen, especially in hours when high electricity demand, thus a higher rate of energy consumption is charged, and consumers are also offered a lower price for the remaining hours (off-hour) [102]. This is due to the inability of utility providers to meet the electricity demand and consequently, the price of electricity will be raised to reduce customer load. If the electricity price stays fixed throughout this peak hour, the demand and supply curves will be imbalanced [103]. CPP specifies the period of the critical peak within an event day, as well as the highest limit of event days annually, but not the exact dates on which the events will take place. As a result, consumers can substantially lower their electricity bill during CPP events through the limitation of load consumption [104]. A case study conducted in [105] showed that residential consumers exhibit a positive effect of demand response in time of CPP event, resulting in a reduction of power consumption. Several advantages of CPP include being easily implemented because it is based on the rate structure of TOU and additionally can enhance the responsiveness of the customer's price by imposing an extremely high rate during critical peak periods [106].

3) REAL TIME PRICING (RTP)

The most complex pricing approach is RTP since the price is established instantaneously according to the supply and demand of the market, resulting in hourly price fluctuations. RTP holds the highest risk with the highest reward to consumers compared to TOU and CPP [107]. Generally, the RTP may be implemented in residential in two ways: (1) as retail pricing signals, and (2) as an integral element of the home energy management systems operation [108]. RTP relies heavily on enabling technology because it must be strongly linked to wholesale market prices and consumer response to allow two side communication. Therefore, enabling technologies such as smart meters are commonly used in RTP to support measurement accuracy [109]. Currently, RTP is more adapted to the electricity supply because of the high penetration of renewable energy like wind and solar into the energy mix, which has caused the balancing of the system to be more complex, thus it would be beneficial to have customer response to wholesale electricity pricing [110].

4) INCLINING BLOCK RATES (IBR)

IBR pricing, as mentioned in the literature, as the demand charge sets a limit on end-user electricity use. If current usage exceeds the stated threshold in a specific period, the consumer will be charged more than the standard rate in that period [111]. In return, the consumers can receive incentives when distributing the energy consumption at different hours throughout the day to save costs and avoid paying higher electricity prices. Currently, utility companies such as San Diego Gas & Electric, Pacific Gas & Electric, and Southern California Edison offer two-level residential rate structures in which the marginal price in the second level (the higher block) is 80% or higher than the marginal price in the first level (the lower block), depending on the utility. Likewise, the British Columbia Hydro Company in Canada has a two-tier conservation pricing structure, with the second level charged 40% more [112]. A case study conducted in [113] showed that the time-variant tariffs (TOU, CPP, and RTP) give more electricity bill savings compared to time-invariant tariffs (flat tariff and IBR) with the deployment of PV rooftops. Therefore, the authors in [114] evaluate a combination mechanism of IBR and TOU to mitigate the cost imposed by IBR when the output of PV generation is deficient with batteries.

B. INCENTIVE BASED-PROGRAM

In incentive-based schemes, the utility can monitor and manage end-user appliances and provide financial incentives for

TABLE 2. List of some PSO variants with their characteristic and mathematical formulation.

Ref	PSO Variants	Characteristics	Mathematical formulation
[78]	Comprehensive Learning PSO (CLPSO)	Each dimension of a particle in general can learn from different p_{best} for different dimensions for a few generations	New updating velocity equation: $V_i^d = \omega \cdot v_i^d + c \cdot r_1 (Pbest_{fi(d)}^d - x_i^d)$ where $f_i = [f_i(1), f_i(2), \ldots\ldots f_i(D)]$ defines which particles' pbests, the particle i should follow
[79]	Adaptive mutant PSO (AMPSO)	The adaptive inertia weight (ω) and the mutation factor ($V_m^d(\tau)$) are combined into the velocity formula to have stronger fitting and simulation capabilities	Updated velocity formula: $V_k^d(\tau+1) = \omega V_k^d(\tau) + C_1 r_1 \left(p_k^d - X_k^d(\tau)\right) + C_2 r_2 \left(p_g^d - X_k^d(\tau)\right) + V_m^d(\tau))$
[80]	Evolutionary PSO (EPSO)	The weights (ω_{ik}^*) of the particle are subjected to mutation while the global best (b_g) comes randomly distributed	$\omega_{ik}^* = \omega_{i1} + \tau N(0,1)$ $b_g^* = b_g + \tau' N(0,1)$ N (0,1) = a random variable with Gaussian distribution with 0 mean and variance 1, τ and τ' = learning parameters
[81]	Cooperative PSO	The vector is split into its component so that n swarms (of s particles) each are optimizing a 1-D vector, instead of having one swarm (of s particles) trying to find the optimal n-dimensional vector	B(j,z)= $(P_1.\hat{\mathbf{y}}, P_2.\hat{\mathbf{y}}, \ldots, P_{j-1}.\hat{\mathbf{y}}, z, P_{j+1}.\hat{\mathbf{y}}, \ldots P_n.\hat{\mathbf{y}})$ Create and initialize n one-dimensional PSOs: $P_j, j \in [1,.n]$
[82]	Binary PSO (BPSO)	The velocity is regarded as the probability that a position takes the value 1 or 0	The position of each particle = $x_{id} = \begin{cases} 1, rand() < s(v_{id}) \\ 0, otherwise \end{cases}$ $rand()$ = uniformly distributed random number in [0,1] $s(v_{id})$ = sigmoid function to transform the velocity to the probability
[83]	Quantum PSO	The state of a particle is shown by wave function $\Psi(x,t)$ of the Schrodinger equation instead of position and velocity	$x_i^{k+1} = P + \beta \cdot \lvert mbest - x_i^k \rvert \cdot \ln\left(\frac{1}{u}\right)\ if\ h \geq 0.5$ $x_i^{k+1} = P - \beta \cdot \lvert mbest - x_i^k \rvert \cdot \ln\left(\frac{1}{u}\right)\ if\ h < 0.5$ u and h = values generated according to a uniform probability distribution in the range (0,1) β = contraction expansion coefficient $mbest$ = mean of the best positions of all particles
[84]	Quadratic BPSO	The introduction of V-shaped transfer functions where only the absolute velocity influences the output of the transfer function	Particle position update: $X_{jd} = \begin{cases} \overline{X_{jd}}\ if\ rand < TF(V_{jd}) \\ X_{jd}\ otherwise \end{cases}$ $TF(V_{jd}) = \begin{cases} \left(\frac{V_{jd}}{0.5V_{dmax}}\right)^2 & if\ V_{jd} < 0.5V_{dmax} \\ 1\ if\ V_{jd} \geq 0.5V_{dmax} \end{cases}$
[85]	Speed-constrained Multi-objective PSO (SMOPSO)	Clerc and Kennedy's constriction factor, χ is adopted to control the particles' velocity which guarantees convergence and avoids large values	$\chi = 2/(2 - \varphi - \sqrt{\varphi^2 - 4\varphi})$ Where $\varphi = \begin{cases} C_1 + C_2\ if\ C_1 + C_2 > 4 \\ 0\ if\ C_1 + C_2 \leq 4 \end{cases}$
[86], [87]	Simulated annealing PSO (SAPSO)	The current global best position is improved using the temperature equilibrium loop of the SA while the temperature is updated using the adopted cooling schedule in the main loop of PSO	$T_0 = f(p_i)/ln5$ $T_{i+1} = R_T T_i$ T_0 = initial temperature ($T_0 > 0$) R_T = positive constant is usually taken in the interval of 0.8-0.999
[88]	Enhanced leader PSO (ELPSO)	Five successive mutation operators are applied to the swarm leader at each iteration. After applying each mutation, if the mutated P_g (global best) has better objective value than the current P_g, it takes the position of the current P_g	First stage: Gaussian mutation $P_{g1}(d) = P_g(d) + \left(X_{max}(d) - X_{min}(d)\right)$. Gaussian(o,a)ford = 1,2,….n Second stage: Cauchy mutation $P_{g2}(d) = P_g(d) + \left(X_{max}(d) - X_{min}(d)\right)$.Cauchy(o,s)ford = 1,2,….n Third stage: Opposition-based mutation $P_{g3}(d) = X_{min}(d) + X_{max}(d) - P_g(d)$ Fourth stage: Opposition-based mutation $P_{g4} = X_{min} + X_{max} - P_g$ Fifth stage: DE-based mutation operator $P_{g5} = P_g + F(X_e - X_q)$

peak-hour demand reduction to engaged customers, and consumers receive a discount rate for their participation. The following are the main scheme under this program:

1) DIRECT LOAD CONTROL (DLC)

DLC enables utility companies to regulate consumer demand remotely by rescheduling or switching on and off certain household appliances. In exchange for the inconvenience caused to the consumer, the utility provides an incentive payment or credit. As such, utilities may control lighting, thermal comfort equipment, refrigerators, and pumps. This includes benefits such as more precise estimation, deep monitor for loads that can be reduced during peak periods, and creating effortlessly simple DSM for customers [115]. A case study of residential DLC control mechanism on air- conditioning (AC) has been investigated in [116] which has given impacts on the demand and environment side through reductions of peak load and CO_2 emission. Nonetheless, issues about a large number of devices and customer security have been significant obstacles to the introduction of DLC [117]. To overcome this problem, the authors in [118] proposed an active database for the DLC system to control automatically the on and off status of the consumer load without the intervention of the operator.

2) INTERRUPTIBLE/CURTAILMENT LOADS

The option for curtailing load during system outages is included in retail tariffs with a discount rate or bill credit by lowering the load consumption. Failure to curb may result in penalties. Usually, interruptible programs were only available to the largest industrial (or commercial) users. However, industrial customers with continuous processes might not be suitable for this program [119]. The least sizes of customers required for interruptible/reduced rates for the standard interruptible program range from 200 kW to 3 MW, depending on the condition and market. Under these tariffs, consumers commit to either reduce the consumption to a predetermined threshold or reduce certain blocks of electricity load. Normally they are required to curtail between 30-60 minutes after being informed by the utility, which is typically done through AMI. However, there is a limitation on the number of times or hours for the utility to request an interruption (less than 200 hours annually) [120]. Therefore, by lowering its peak demand, the utility saves money on expensive power reserves, improves service quality, and ensures reliability. Customers benefit from lower energy costs and incentives offered by the ISO or the local utility [121].

3) EMERGENCY DR PROGRAMS (EDR)

Emergency DR systems offer consumers incentive payments for lowering their demand voluntarily when durability- triggered events occur. However, consumers have the option of foregoing payment and not curtailing when notified. Furthermore, no reduction in consumers for their load consumption will not be punished. Typically, the amount of the incentive rewards is determined in advance [122]. In the case of the wholesale market, the Independent System Operator (ISO) will adopt EDR programs to lower peak demand and prevent price spikes [123]. A big number of customers voluntarily participate in the EDR program in response to ISO's announcement [124]. As an incentive, the customers will receive a huge amount of money as a payment of approximately 10 times the off-peak electricity price by ISO [125]. For example, in the United States, the New York Independent System Operator (NYISO) provides two EDR programs which are NYISO-EDRP and NYISO-SCR (special case resource) to respond to NYISO operating instructions by reducing load when operating reserves are expected in low conditions or during an emergency of a system [126].

4) DEMAND BIDDING PROGRAMS

In DBP, the opportunity is given to consumers by the electricity trading markets to select a time and way for real-time and day-ahead spot market participation. Thus, by removing the load, the consumer will receive a market price when the market operator requests it, similar to the payment for generators to supply. Customers will negotiate on a certain price decrease, timeline, and availability, and their offers will be filtered and chosen according to market demand. In most cases, for the highest accepted bid offer or for developing demand-side bidding markets, a minimum fixed rate will be paid to all bidders [126]. For example, the Quick Bidding Program (QBP) is proposed by [127] in Kuwait with features that the targeted reduction load by the utilities will be displayed on their websites within the time frame. Consumers can quote their capability to lower the load for different periods. Meanwhile, a practical example of this bidding mechanism is the NYISO's Day-Ahead Demand Response Program (DADRP) which allows the consumers to bid their load reductions into the Day- Ahead energy markets as generators do. The payment of offers that are determined to be economic is paid at the market clearing price [128].

C. PSO-BASED APPLICATIONS IN DEMAND RESPONSE

The main attributes of each relevant research work are presented in Table 3. PSO is an effective way of solving large-scale non-linear optimization problems [129]. The reason for practicing PSO in DR optimization is because of the tendency to give impactful and accurate results [130]. It can quickly locate a near-optimal solution while requiring less effort than other mathematical methods for solving a non-linear optimization problem in DR. Moreover, PSO is the most commonly used optimization algorithm for solving DR optimization problems [94], [131]. Thus, it is proposed to address the DR management problem in the present works. From the observation, the authors mostly investigate the working of PSO models in the different DR programs based on one or more optimization objectives: (1) energy or electricity cost minimization, (2) peak-to-average ratio (PAR) minimization, (3) peak load reduction, (4) maximize operation profit and

(5) maximize the use of renewable energy resources (RER) while considering user comfort. This is important to attract the consumer to respond or participate in DR programs when several constraints such as temperature regulation, optimal state of charge (SOC) for EV or energy storage system (ESS), and favorable timing for appliance use are applied. Moreover, the integration of RERs such as wind and photovoltaic (PV) solar with ESS, EV, and the battery has been studied in most of the research works to achieve those objectives when the charging is during off-peak hours while discharging is during peak hour in response to DR pricing or incentives.

IV. CLASSIFICATION OF ENERGY EFFICIENCY

A. ENERGY EFFICIENCY IN BUILDINGS

Energy efficiency (EE) can be defined as a long-term conservation strategy that aims to save energy and reduce demand through energy-efficient processes [155]. Energy efficiency gives huge benefits such as the reduction in the required number of energy resources to achieve a specific amount of energy service, along with associated effects on depletion of resources, energy safety, and cost-saving; as well as the decrease of carbon emissions, other pollutant emissions, and overall environmental impact linked with electricity consumption [156]. According to the Efficient World Scenario (EWS), energy efficiency may lower yearly energy-related emissions by 3.5 GtCO$_2$-eq (12%) based on 2017 levels, accounting for reductions greater than 40% of the reductions necessary to comply with the Paris Agreement [157]. Therefore, the combination of energy efficiency with renewable energy and other measures is critical to achieving the target of global climate. Generally, EE practices in buildings consist of 1) active measures: optimizing the HVAC system, energy-efficient appliances, and lighting, renewable energy utilization, and managing the energy effectively with regards to occupant's comfort and 2) passive measures: lowering energy consumption by utilizing the potential of nature's lighting, cooling, and heating [158]. The EE in buildings is determined by several factors such as the degree of electrification, the level of industrialization, the amount of building area per capita, the existing climate, and policies at a local and national level to promote energy efficiency [159].

Another action under the EE strategy is energy conservation (EC) which focuses on changing the behavior of people to utilize energy more efficiently. In the energy pyramid, EC is the first step to achieving sustainable energy as it is located at the base with the least cost option [160]. The conservation of energy in residential can be implemented either by changing the consumption of energy services or spending on energy-efficient appliances [161]. In general, EC behaviors are continual and repetitive actions to reduce consumption daily that requires compromising comforts or reducing economic utility to save energy driven by several factors such as social-psychological and environmental concerns [162]. Energy conservation measures (ECM) in buildings are classified into three types: major investments, minor investments, and zero investments. ECMs have recently drawn increased attention due to their useful application in both newly constructed and existing structures. Initially, the potential of energy-saving for ECMs is assessed by simulations, and then the appropriate ECMs are chosen for implementation in actual buildings [163]. Several passive measures, such as insulation on a residential house [164] show significant energy-saving potential and collectively reduce the energy performance index (EPI) by 34%. The insulation of a building may maintain the cool or heat of the house internally while restraining heat flux with the surroundings since the thermal insulator material can reduce the rate of heat flow [165]. In comparison, the active measures taken in [166] could reduce energy by 63.5% in EPI, which is significant savings obtained through the replacement of ordinary appliances with energy-efficient appliances. Moreover, the modelling results in [167] show that the most effective way to reduce evening peak demands is by switching light bulbs to LED, which results in reductions of total appliance electricity demand by 18.8%, total residential electricity demand by 14.2%, and total national electricity demand by 5%. Whereas authors in [168] adopted both active and passive measures in buildings and discovered that installing PV systems and decreasing lighting power density had the best energy-saving ratio.

B. MEASUREMENT AND VERIFICATIONS (M&V)

Measurement and verification (M&V) are necessary to test the performance of each energy conservation measure to ensure its efficient implementation and operation. M&V is a process of employing measurements to accurately identify the energy savings achieved by an energy efficiency intervention in a specific building or facility. The energy savings reflect the absence of energy consumption, so they cannot be analyzed instantly, thus, the evaluation is usually made through a comparison of energy consumption at the facility before and after the adoption of a retrofit measure, keeping any changes in circumstances [169]. The major purpose of M&V is maximizing the accuracy of energy savings, optimizing financial efficiency projects, increasing the public understanding of energy management, and addressing the significance of emission-reduction credit [170]. Part of the M&V methodologies to be followed is fitting and maintenance of meter calibration, collection and analysis of data and justifiable results, and verification of reports [171]. The International Performance Measurement & Verification Protocol (IPMVP) defines four different M&V options: partially measured retrofit isolation (A), retrofit isolation (B), whole facility (C), and calibrated simulation (D) [172].

In any M&V project, three periods occur sequentially, consisting of the baseline, implementation, and reporting periods. The engineering or statistical methods are usually performed to estimate the adjusted baseline in the reporting period by normalization calculation [173]. Therefore, it is important to maintain its accuracy and minimized the uncertainty throughout the process to determine its success.

TABLE 3. Research works on PSO-based applications in the DR program.

Ref	DR Program	PSO-based method	Objective function	Constraints	Key Findings
[132]	RTP	Binary PSO (BPSO)	To minimize the electricity cost, system PAR and user's discomfort with the integration of PV, ESS and EV in HEMS	The charging and discharging of ESS and EV based on RTP pricing, current, and maximum SOC, power demand limit and availability of EV	Cost reduction by 52.47% from the base schedule price, while the PAR and DI were reduced by 15.11% and 16.67% respectively through optimal scheduling by BPSO
[133]	RTP	Binary PSO (BPSO)	To minimize the electricity bill for prosumers and consumers (PV & wind, and EV) through Peer to Peer (P2P) energy trading in the smart home	Power balance, appliances operation, the charging and discharging of battery and EV	The electricity cost minimization is achieved through optimal scheduling of appliances and utilizing P2P energy trading when the excess power of DG is traded to consumers instead of the grid
[134]	TOU	Hybrid PSO	To minimize the energy cost and total tardiness in the flexible flow shop scheduling for the multi-objective optimization	Completion time and job processing	The total tardiness and the electric power cost are minimized simultaneously while maintaining production efficiency by reducing the machine speed and higher electricity consumption at off-peak times
[135]	CPP and RTP	Multi-objective PSO (MOPSO)	Reduction of energy cost and PAR while maximizing user comfort in HEMS with the integration of RES	Operating time of shiftable devices and their usage	RTP gives greater electricity cost savings compared to CPP
[136]	TOU and developing TOU (D-TOU)	PSO	Reduction in building peak load and customer electricity cost with optimized thermal energy storage (TES)	TES system capacity and its operation	Load shifting and reduction of peak load for utility and cost reductions obtained by a customer with an optimally configured TES system
[137]	CPP, DLC, TOU, RTP, Interruptible	PSO	To minimize the generating costs along with the operating cost considered DR programs-based unit commitment	Price elasticity of demand and welfare functions of customers	CPP and DLC give the maximum reduction of peak demand while TOU shows the highest reduction in the total cost
[138]	CPP, TOU	PSO	To maximize the profit in manufacturing considering the electricity and labor cost	Production target	During summer, the load curve of profit under CPP is greater than the load curve of profit under TOU
[139]	TOU	Multi-sub swarms PSO (MSPSO)	To minimize the monthly electricity charge for commercial building	Particle velocity and particle position	As compared to PSO, MSPSO could save approximately 17% on monthly charges when peak load is reduced during on-peak periods in the scheduling simulation
[140]	TOU	Binary PSO (BPSO)	To find the best sizing and placement for electrical energy storage devices (EESDs) on an improved IEEE 24 bus test system in smart grids	Sizes of the EESDs and the budget for investments in EESDs	Load factor improvement and cost reduction with DR program associated with EESDs since during the load demand is reduced and shifted to valley periods.
[141]	CPP, RTP, TOU	PSO	Minimization of cost for operation, pollutant treatment, and carbon emission in household energy management under different RER and EV	Distributed energy resources sizing, power balance, distributed generation power limits, exchanging power limits, EV charging and discharging limit, ramp rate limit, and line transmission capacity	The overall result shows that the proposed approach achieved the objectives and provide a good solution while maximizing RERs and EVs integration under DR programs during summer and winter

TABLE 3. ***(Continued.)*** **Research works on PSO-based applications in the DR program.**

[142]	Enhanced TOU (ETOU)	Evolutionary PSO (EPSO)	To reduce the electricity cost for electronic manufacturing facilities through simultaneous load management strategies	Total energy consumption before and after the optimization should not be more than 5%	Reduction of monthly electricity cost gain when the maximum demand value located in the mid-peak zone and peak demand value was decreased
[143]	Curtailment load	Quadratic PSO (QPSO)	To solve the unit commitment in DR with the integration of microgrid (MG) considering the uncertainties	Minimum spinning reserve, operational of MG	The DR integration into MG reduced its operation cost by 15.31%
[144]	EDR, Interruptible, DLC, TOU	PSO	To minimize the cost of purchasing and energy supply production with the integration of RES as well as maximization of financial profit for microgrid	The total power produced by RER, the main grid, and the generator must be equal to the sum of power needed for two consumers	The energy reduction, total compensation, and incentive savings achieved due to load shifting from peak to off-peak periods
[145]	DLC	Binary PSO (BPSO)	To increase the temperature of the water heater over 24 hours while reducing the total peak load demand for the residential load	The weight factor for temperature is bigger than the total load weight for customer satisfaction	Peak load reduction for about 500W-750W per household and obtained potential cost savings for utility and household user
[146]	Interruptible	Binary PSO (BPSO)	To meet a requirement of a system for total curtailments in an hour while minimizing both total payment and the frequency of interruptions imposed on customers	Operational of the available interruptible loads	BPSO can solve a multi-objective optimization problem, minimizing objective functions, and the number of interruptions is reduced and distributed across all loads
[147]	Interruptible	Improved Cooperative PSO (ICPSO)	To optimize the profits for the operation of a virtual power plant (VPP) and VPP model of energy management while maintaining the comfort of the occupant	Conventional unit, ESS charging and discharging, Flexible load adjustment, energy supply, and demand matching	Increased operation profit by 10.82 and 2.38%, respectively, in comparison to the optimization approach that solely took into account interruptible and rigid load
[148]	RTP	Binary PSO (BPSO)	Minimization of energy cost, carbon emission, PAR, and occupant discomfort considering RESs and ESSs	Operation of residential appliances, charging/discharging of ESS	Decrement in cost (2.89%), PAR (18.75%) carbon emission (14.9%) compared to unscheduled with the presence of RESs and ESSs
[149]	TOU	PSO and Improved PSO (IPSO)	To reduce the total electricity cost and PAR integrated with Plug-in Electric Vehicle (PEV) through an effective approach of sharing economic scheme in a community	The amount of selling power, batteries operation, and the total energy supplied less or equal to the power consumption of the building	Reduction by 23% of electricity cost for each home and 37% of peak demand and PAR for the total community
[150]	Interruptible	Multi-objective variants of PSO (MOPSO)	To optimize the size of a hybrid system consisting of PV and diesel generator through load variation factor (LVF)	Maximum number of system components and maximum value of LVF	An affordable and dependable hybrid energy system consists of a PV panel and diesel generator with optimal load reduction portion
[151]	EDR	PSO	To optimize the EDR model of central air-conditioning (CAC) simulating consumers' trade-off between thermal comfort levels (TCLs) and profits	The indoor temperature at the initial time and the preference of consumers	The increase in the penalty prices is more significant compared to the increase in compensation prices for the EDR level of CAC improvement
[152]	EDR	PSO	To coordinate convenience and economy by planning the energy use of the user's indoor equipment in a HEMS with scattered generations	The working characteristics of appliances, user preferences, charging/discharging power of energy storage equipment	Under different EDR incentives, user-obtained load reduction and cost benefits prove the solution scheme can solve home energy scheduling problems under uncertain environment

TABLE 3. ***(Continued.)*** **Research works on PSO-based applications in the DR program.**

[153]	TOU, RTP, Curtailment load	Enhanced Leader PSO (ELPSO)	Optimal scheduling of HEMS & bill reduction	The range for starting time of each appliance, time intervals for appliances to ON in a day	• Greater reduction of consumer's electricity bills while maintaining their convenience • ELPSO outperforms other basic models
[154]	TOU	Simulated annealing PSO (SAPSO)	To reduce the peak load under TOU pricing optimization	User's benefit, benefit to the power supplier, electricity rate, marginal cost price, electricity consumption similarity, total electricity consumption	The proposed method maintains the satisfaction level and power consumption of consumers while decreasing peak load and increasing valley load.

Measurement, sampling, and modelling are the three key uncertainty elements to consider when reporting savings with reasonable statistical precision [174]. The acceptable levels of uncertainty are determined by the point at which savings are greater than twice the baseline model's standard error, according to the IPMVP, which offers a systematic methodology for assessing each element of uncertainty added to a project [175].

The simulation-based method in Option D necessitates model calibration using measured data in an hour or month. The recommended process to verify the whole building or specific building components for its performance and verification used is calibration simulation, which is included in Option D [176]. Building energy models are often calibrated by incrementally changing parameters of the model from audit data until predicted energy use is within specified tolerances from actual measurements. The parameters that have the greatest influence on the major indicators of building energy performance predicted by the model are often identified through uncertainty and sensitivity analyses, and during the calibration process, these parameters receive heavier weightage [177]. The acceptable tolerances for the validation of building energy models are outlined by IPMVP [178] and ASHRAE Guide 14 [179]. Nowadays, automated calibration has gained interest compared to conventional methods due to its faster and more efficient processes such as Bayesian calibration [180], pattern-based calibration [181], and multi-stage calibration [182]. Furthermore, the revolution of M&V 2.0 has offered new technologies that might lower the cost of M&V, generate quicker findings with greater transparency and confidence, and thus raise the acceptability of the savings projections [183]. More advanced technologies of M&V 2.0 tools that have been commercially available in the market have been discussed in [184].

C. ENERGY MANAGEMENT SYSTEM (EMS)

The definition of EMS is a computer system consisting of a software platform for basic support services and a collection of applications for the functionality required to ensure sufficient energy supply security with minimal price and efficient operation of electrical generation and transmission facilities [185]. The purpose of EMS is to optimally distribute various energy sources to consumers while integrating renewable energy sources without jeopardizing the system's dependability, security, or safety [186]. The benefits of EMS include low operational costs the privacy of consumers, diversifications, and a less computational load [187]. In the smart grid (SG), the main energy management objectives including EE, demand profile enhancement, cost optimization, and consumer comfort. SG delivers energy more efficiently, improving customer utility interaction, and modern management techniques, and responds to wide-ranged events occurring in the system [188]. Technologies such as human-machine interfaces (HMI) and supervisory, control, and data acquisition (SCADA) are helpful for effective EMS implementation, especially if a certain demand is supplied by more than one energy source. The EMS strategy can be classified into a rule-based approach and an optimization approach as shown in Fig. 4 [189]. The first approach manages the power demand by implementing a fixed rule based on the efficiency maps of the equipment, whereas the latter approach uses the common strategies which are equivalent consumption minimization strategies (ECMS) and model predictive control-based strategies (MPC) [190]. PSO can be used to optimize the structures and parameters of these methods. The current literature reviews the various control and operation strategies of EMS in hybrid renewable energy [191], microgrid [192], and hybrid electric vehicle [193] applications integrated with optimization techniques to have better performance and achieve some objectives.

Meanwhile, the contribution of the home energy management system (HEMS) in the residential sector has been promoted in references [194] and [195] to coordinate and schedule the home appliances according to certain criteria, thus improving the energy efficiency and demand flexibility of the buildings. The several functionalities of HEMS including providing a detailed overview of the graphical data of energy consumption have a few advanced functions for monitoring, information, and automation purposes and to forecast the loads and local generations at the household levels [196]. IoT technologies have been incorporated with HEMS during the past several years and are essential for the intelligent control and management of the system's end users.

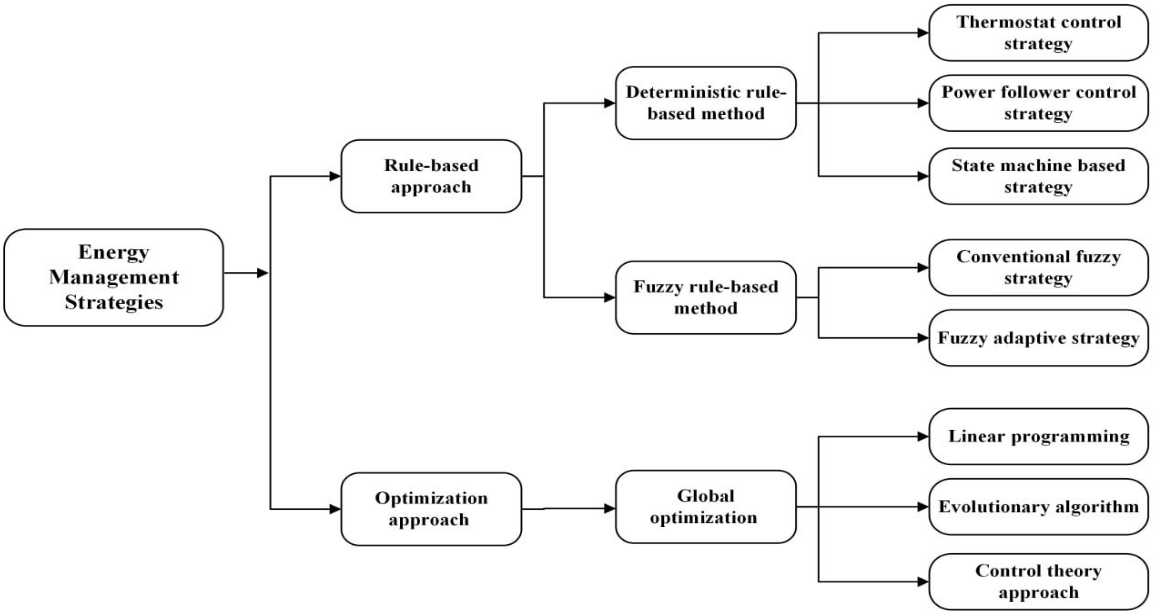

FIGURE 4. EMS strategies classification.

Furthermore, the AI and ML technologies that can be trained and used to forecast the near future are implemented into modern smart houses [197]. A recent study of consumer willingness to adopt HEMS was analyzed in [198] based on different interactions such as technology attributes, attitudes, and infrastructure.

D. PSO-BASED APPLICATIONS IN ENERGY EFFICIENCY

Table 4 presents the research works on energy efficiency with different energy systems. In terms of optimization models, most researchers studied optimizing energy systems and improving energy efficiency by using single or multi-objective PSO models. Without being restricted by the burden of dimensionality, PSO can quickly solve extremely challenging constrained optimization problems [188]. The integration of EE measures with RERs is a promising mechanism that can effectively drive the low-carbon energy transition under practical constraints. Meanwhile, the optimization based on EMS focuses on achieving global optimum by minimizing cost functions such as energy consumption and total cost. Besides, optimization-based calibration has been adopted in the studies and uses accuracy metrics for accuracy measures such as mean average error (MAE), mean bias error (MBE), and coefficient of variation of root mean square error (CV(RMSE)).

V. PSO-BASED ALGORITHMS IN DSM: CHALLENGES AND POTENTIAL SOLUTIONS

The key challenges of implementing PSO in DSM are categorized based on the complexity and uncertainty of the modelling and optimization. The complexity in the modelling is addressed for multi-objective optimization problems considering the large number of parameters used, the system architecture, and constraints. Additionally, due to uncertainties in the optimization process, it is quite challenging for researchers to develop a stochastic model.

A. COMPLEXITY IN MODELING

The complexity of the optimization process directly influences the convergence speed and accuracy of modelling outputs [58]. In the previous work reviews, PSO applications in DR and EE fields show the intermittent penetration of RERs, ESS, EV, and multiple household appliances in load scheduling while considering user preferences. Various PSO-based models are used to determine the optimal schedule for devices to make the scheduling process simpler, however, there is a trade-off between optimality and complexity [222]. The high modelling complexity has increased the risk of infeasibilities or slow convergence. The consideration of multiple classes of load scheduling such as shift, fixed, and interruptible appliances in HEMS caused the longest waiting times for the appliances to shift to the times desired by the consumer [135] and longer convergence times [223], thus increasing user dissatisfaction. In the smart grid, the interruptible loads are bounded by the time duration specified by users, leading to a vast number of potential solutions. Thus, the swarm formulation needs to modify ensuring the solutions are within the user-specified time frames [224]. For large-scale situations, the original PSO model has longer computation times in DSM problems involving PEV charging and discharging [149] and PV systems [225] considering multiple homes in the residential community. Large population sizes and iterations require additional computation and increase both computation time and the algorithm's reliability [226]. In addition, the privacy

TABLE 4. Research works on PSO-based applications in the EE program.

Ref	EE Program	PSO-based method	Objective functions	Constraints	Key findings
[199]	M&V	PSO	To construct accurate baseline models	Data range	The suggested approach is estimated to save M&V costs and time while increasing the calculation's accuracy for energy performance.
[200]	Calibration	PSO	To optimize the existing manual calibration and modify it into an automated process	Input parameters	The automated optimization calibration improves the accuracy and efficiency of the calibration
[201]	Multi-stage building calibration	PSO and hybrid Generalized Pattern Search PSO with Constriction Coefficient Hooke-Jeeves (GPSPSOCCHJ)	To calibrate the different sub-models separately and obtain an accurate model	Calibration error limits	Hourly temperature data had a lower MBE and CV(RMSE) of -3.74 percent and 6.03 percent, respectively
[202]	Fuel cell	Adaptive mutation PSO	To reduce energy consumption and improve output stability	Dynamic response and protection elements	The improvement of lithium battery charging and discharging rationality and fuel cell stability
[203]	Heat pump integrated water heater	Multi-objective PSO	To determine the ideal operating point for the air flow rate and compressor speed	Size of household appliances	Reduction of energy consumption by 16% with a minor increase in noise level and operating time
[204]	Building envelope and air-conditioner	PSO	To minimize annual cooling energy consumption for a residential building	Not specify	• Reduction of annual cooling energy consumption up to 53.78% compared to baseline • PSO is more profitable compared to GA for the simulation of the building optimization process
[205]	Heating load (HL) and cooling load (CL) of HVAC	PSO-Multi-Layer Perceptron (PSO-MLP)	To reduce the HL and CL of residential energy-efficient buildings	Not specify	• The performance of MLP is more efficient with a decrease in MAE and RSME for both load • PSO shows more robustness compared to ABC in optimizing the parameters of MILP
[206]	Operation system	Renewal PSO (RPSO)	To boost system profitability and energy efficiency	Interactions between machines and buffers	The proposed control method showed resilient operation against random disruption events and adapted well to time-variant system reliabilities
[207]	Cooling water system	Hybrid programming-PSO (HP-PSO)	Enhancing the cooling water system's performance	Limits on the cooling tower's outlet water temperature, the range of control for the cooling water pump and cooling tower fan, and the variety of electrical devices	Potential for a 15.3% reduction in the energy used by the cooling water system.
[208]	Building calibration	PSO	To generate lumped parameter-building models with similar dynamics for different ECMs.	Not specify	Models of retrofitted buildings can be calibrated using the suggested approaches with an acceptable degree of accuracy (MAE $\leq$ 0.5°C).

TABLE 4. ***(Continued.)*** **Research works on PSO-based applications in the EE program.**

[209]	Lighting devices	Distributive-PSO (DPSO)	To minimize power and produce sufficient illuminance	Dimming instructions and minimum illuminance	The suggested technique effectively controls luminance in actual for a range of working environments.
[210]	Plug-in hybrid electric vehicle (PHEV)	Multi-objective PSO	To reduce the driver's action on the steering angle, minimize the mass of electrical components, fuel consumption, and exhaust emission	The angular speed of the ICE, gearbox neutral position, RMSE value of the optimized vehicle, PHEV consumption	Reduction of the driver steering action by 71.9%, reduction fuel consumption by 18.44% and reduce pollutant emissions by 69.34% of CO, 20.33% of HC, and 22.11% of NO_x
[211]	Lighting	Multi-objective PSO	To enhance the visual comfort of users and energy savings in a building	Luminaire's dimming average, illuminance level limit, illuminance uniformity	Energy efficiency and illuminance uniformity improved by 58% and 17% respectively compared to the baseline
[212]	Sewage treatment system	PSO	To improve energy efficiency	Not specify	Achieved a good energy-saving effect
[213]	Internal combustion engine	Improved mutation PSO (M-PSO)	Minimization of total cost and CO_2 emission	Energy balance, components operational	The varying weight ratio of the two objectives has a greater impact on the annual total cost-saving rate compared to the annual CO_2 emission reduction rate
[214]	EMS for ship hybrid energy system	Quantum PSO (QPSO)	Low operating costs and optimal use of clean energy for ship electric power systems	Clean energy power generation, energy storage power supply, fuel cell power generation, diesel power generation, and load power balance	• Reduction of operating costs, fuel costs, and pollutant emissions of marine power system • Achieved the environmental requirements of the Energy Efficiency Operating Index (EEOI) for ships
[215]	EMS strategy of hybrid solar-hydro system	PSO	Size optimization based on the levelized cost of energy (LCOE) minimization	The water level in the upper and lower reservoir	Configuration with hybrid PV-battery integrated with pump hydro-storage system has greater power system efficiency and more reduction in LCOE compared to another model
[216]	EMS strategy for PV system and BESS	PSO	Finding the best PV and BESS size given the specified energy cost	SoC of BESS and system operation	The suggested approach can find the most cost-effective sizes for PV and BESS
[217]	EMS of microgrid for virtual power plant (VPP)	Multi-objective feasibility enhanced PSO (MOFEPSO)	To reduce the total operating cost and net emission	Power balance, storage limits	The proposed method reduces the operating cost, and GHG emissions and optimized the scheduling operation of microgrid for VPP
[218]	EMS for fuel cell hybrid power system	PSO	To make the proton exchange membrane fuel cell (PEMFC) hybrid welding robot system more stable for real-time performance and economical	SoC of lithium battery, fuel cell output power	The stability of fuel cell power output is improved by 11.26% and reduction of hydrogen consumption by 3.24%
[219]	HVAC	PSO	To propose a new approach to optimizing HVAC energy consumption based on a prediction of load and energy flexibility	Prediction of chiller loads	The discounted payback value is 5.8 years, and the energy-saving ratio is roughly 10%
[220]	EMS for microgrid of building prosumers	PSO	To minimize the operation cost in the building integrated with RES, ESS, and PEVs	Operation and technical of the buildings	• Achieved cost savings in the range of 11% • Lower nominal power of the HVAC system can be used
[221]	HVAC	Artificial Neural Network (ANN)-PSO	To ensure optimal operation of the HVAC system and control indoor environmental parameters	Indoor air temperature, indoor air humidity, indoor air CO_2, indoor air volatile (VOC)	7% overall energy reduction without deteriorating the conditions of the internal environment

issues of individual homes in the community should be a concern for the optimization process where the system design should not collect power usage profiles of all users in centralized ways. Thus, the practical optimization model must be modelled concerning privacy issues and other parameters like cost and carbon emission [227].

The standard PSO is only suitable for the optimization problems in continuous space, thus its variant model for a discrete domain such as discrete PSO (DPSO) and binary PSO (BPSO) are proposed for the combinatorial optimization problems in discrete space, in which the trajectories of particles are defined as the changes in the probability and the velocity is transformed from real number space to probability space via a sigmoid function. Moreover, HEMS-based scheduling often required binary formulation for the ON and OFF status of the appliances and a large number of decision factors, thus the optimization problem would be more difficult than the problem with integer decision variables [84]. The DPSO algorithm is able of creating adequate diversity during the search, although it frequently suffers from the disadvantage of being trapped in local optima [134]. Thereby a hybridization of variant PSO models such as hybrid BPSO and GA (HBPSO) [228] and hybrid DPSO [134] are proposed for more complex problems. The multi-objective optimization which is more complex than the single optimization problem often involves constraints and user preferences, thus the solution to the problem is a challenging task. Considering user comfort would lead to an increase in cost and PAR when optimizing the three parameters together in a multi-objective problem [229]. Therefore, requires a search for the best trade-off between these objectives by adjusting the weighting coefficients in different cases to find the best possible solution [132].

VPP energy management is similarly a challenging task because of the coordinated functioning of various energy supplies and the associated uncertainties which requires an optimal algorithm to ensure smooth and reliable operation in real-time without sacrificing the optimal operation costs. A basic PSO model suffers from early stagnation and loses exploration capabilities during the latter evolution stage when addressing the complicated issue, thus, a hybrid PSO may be developed to minimize the iteration number. PSO model suffers from premature stagnation and loses exploration ability during the later evolution period while solving the complex problem, thus a hybrid PSO can be utilized to lesser the iterations number when real-time data is used [230]. Furthermore, when basic PSO integrated with a time-varying acceleration coefficient (PSO-TVAC) dealing with complex problems such as optimization of the operation and schedule of air conditioning system under different conditions, it is very difficult to search for a feasible solution directed to more trouble if the scheduling constraints are considered in the early stage of iteration [231]. Thus, the modified PSO (MPSO-TVAC) method is introduced to increase the exploration ability and rate of success for a global optimum by including a ''random viable solution'' into the standard PSO-TVAC.

B. UNCERTAINTY IN OPTIMIZATION

In the optimization process, the consideration of uncertainty directly reflects the uncertainty in real-life problems, which might impact model results and the optimum value of the objective function. Therefore, any global optimization search includes an addition element of uncertainty [232]. The motivation to develop stochastic modeling in DSM stems from the challenge of confronting the uncertainty and fluctuation of RERs, dynamic pricing of tariffs, environmental variables, and random user behavior. The issue with stochastic variables is their deterministic constraints. Under such conditions, uncertainty is diminished to a certain extent [233]. Thus, robust optimization has shown to be a promising technique for addressing the uncertainties in the optimization issue problem. Authors in [234] consider the uncertainty of production from wind and PV panels to solve the day-ahead energy management in buildings. In order to introduce higher exploratory properties in the search procedure, the fixed parameters in the traditional MOPSO are modified into a mutation of the strategic parameters in EPSO. This adjustment increased the cover rate and the overall front of the non-dominated solutions. In view of the shortcomings of PSO such as lack of randomness in particle position changes and numerous parameters, the theory of quantum mechanics is combined with PSO to solve the non-linear and non-convex optimization problem considering high uncertainty from the power output of PV and wind turbine in microgrid [235]. The optimal scheduling method for power resources in microgrid considering the uncertainty of renewable energy output is vital especially when the generation of actual maximum power from wind and PV is less than the power arranged in the scheduling plan, increasing operating costs and frequency fluctuation of the microgrid which may harm the system [236]. Moreover, the imprecise prediction of RERs generation output directly led to non-optimal energy management and programming, and increase households' electricity costs, thereby restricting the benefits of smart homes [237].

Dynamic pricing schemes like RTP has the potential to reward consumer fully but it also has the potential to maximize risk when they are unable to manage the use of electricity prices depending on the predetermined interval [238]. Due to hourly price changes, RTP flexibility may reflect load patterns or generating costs. RTP is more flexible than both TOU and CPP, but it has the disadvantage of consolidating numerous appliances in low-cost energy zones. To handle it, the author in [239] presented a system by combining IBR and RTP to adjust energy price rates during the low energy price period depending on appliance power consumption. When the overlapping time of appliances is customized with IBR, the fitness function of PSO integrates a modified IBR to

TABLE 5. Opportunities for new application under DSM.

Ref	New application	Suggested PSO-based method
[242]	Integrating EVs along with distributed generation into the energy management problem	MPSO
[243]	Optimizing the CO_2 and $PM_{2.5}$ concentrations simultaneously in the real building	Back-propagation neural network combined with adaptive multi-objective PSO (BPNN-AMOPSO) based on computational fluid dynamics
[244]	• Trigeneration system of electricity, cold and heat • Cold applications such as refrigeration or deep-freezing	Not specified
[245]	Integration for load forecasting results for individual end users to observe the overall forecast accuracy for a community and the effect of combining load forecasts and HEMS for the whole community	Not specified
[246]	Combination of energy management strategy and the flat controller by including the controller parameter in optimizer as optimization variables	Not specified
[136]	The determination of optimal electricity prices for industrial loads based on dividing weekdays into smaller periods, namely super off-peak, off-peak, peak, on peak and super on the peak in conjunction with partial and full storage capacities for thermal energy storage system	Not specified
[247]	The integration of electrical energy storage and the price of real estate from the perspective of a win-win situation between consumers and investors	Not specified
[248]	The steering system energy savings with the influences of the steering assist characteristic and design of the variable assist characteristic curve based on maneuverability and energy savings	Shuffled PSO (SPSO)
[249]	Economic dispatch problem associated with power system operations as well as the convergence characteristic	Double-weighted PSO (DWPSO)
[250]	• The optimization of peak grid load more directly and grid carbon intensity reductions by optimizing costs and the system's carbon footprint in combination • Energy sharing in smart, connected communities with energy storage systems • Detailed modelling of the techno-economic feasibility of different battery chemistries (including storage capacity in EV) • Assigning the use of the different zones in the building to different user types based on their specific thermal preference	Not specified
[251]	• The energy consumption characteristic of the unit coupled with a heat pump or heat storage tank • Optimization of thermal power load distribution among the modified units based on the energy consumption characteristics	Momentum PSO (MPSO)
[252]	Creating a generalized model feasible for other locations and layouts in the country and beyond for the hybrid renewable energy systems	Not specified
[253]	Different types of liquid air energy storage systems	Not specified
[254]	• Comprehensive analysis of evaluating self-discharge as a parameter varying with temperature in the energy storage system • Considering the effect of environmental parameters on the design of the configurations as optimization objectives • Pump hydro storage operation for switching between two energy storages by varying the proposed parameters	Not specified
[255]	Multi-generation energy systems with different energy technologies to any case studies such as buildings, universities, and district	PSO-DP (dynamic programming)
[256]	Optimal design for fast EV charging stations with wind, PV power, and energy storage system in the operating cycle of a week, month, or year	Combining MOPSO with other searching algorithms such as harmony search and cuckoo search
[257]	More complex non-linear and binary energy management problems	Constraint PSO-based MPC (model predictive control)
[130]	Integration of battery storage system to overcome the uncertainty of RERs in microgrid	Hybrid PSO optimization techniques

TABLE 5. ***(Continued.)*** **Opportunities for new application under DSM.**

[258]	Integration of different RESs and storage options to enhance the reliability of the power system	Not specified
[259]	• The scheduling of DSM through the coordination among different sectors in the presence of power grid, RE, ESS, and EV by embedding sensors and Internet of Things (IoT) modules in each participant • Fog and cloud-based DSM employ various DR programs to achieve the desired balance between demand and supply • Engagement of advanced, intelligent, and loads that have time as well as power flexibility for efficient energy management	Hybrid bacterial foraging and particle swarm optimization (HBFPSO)
[260]	Increasing the number of customers, service providers, and industrial consumers considering the effect of integrating RES on the multi-stage incentive-based demand response program	Stackelberg-PSO
[261]	• Optimal powertrain sizing considering plug-in charging with SoC depleting mode (plug-in HEV) or zero urban emission zone running with electric-only operation in the urban part of the vehicle energy consumption calculation tool interurban cycle • The effect of changing component size on vehicle mass and the corresponding variation in vehicle tractive resistance, power consumption, and optimally sized powertrain solution	Not specified

lower PAR. Meanwhile, authors in [240] introduced interval number optimization for constraint violation based on tolerance degree to tackle minor uncertainty in residential load scheduling related to human behavior and weather conditions by combining PSO with an integer linear programming method. Considering the limitation of transforming the uncertain into a certain optimization, an extra function or information, such as probability distribution in stochastic programming, must be incorporated into household load scheduling, resulting in difficulty of optimization and demand for a large quantity of historical data. In specific scenarios, collecting data for a new home or in the absence of measurement instruments is challenging [240]. Furthermore, uncertainties about some input data, such as active and reactive load demands, as well as the unpredictable behavior of EV owners create unparalleled reliability and security issues to the overall distribution network. Therefore, probabilistic studies with a high degree of precision and tractable algorithms are necessary for the evaluation of uncertain behavior toward output variables of power system safety and balance operation [241].

VI. OPPORTUNITIES FOR NEW APPLICATION UNDER DSM

The previous literature reviews the significant work which has been conducted in the energy optimization field for different categories of DSM. Nevertheless, there are new applications that need to be explored as suggested in recent publications, so that the PSO-based method can be more relevant and developed in the real-life application of DSM. Thus, it can attract more consumers to participate and engage with the programs offered. Table 5 outlined new applications under DSM for opportunities to further research.

VII. CONCLUSION AND RECOMMENDATIONS

The effective implementation of DSM can encourage the production of low-cost, high-quality, and excellent services to consumers in addition to promoting supply-demand balance. This review paper presents a comprehensive overview of DSM activities in demand response and energy efficiency specifically. From the thorough review, DSM activities have facilitated in solving many of the challenges such as high electricity bills during peak hours, load curtailment in industrial buildings, and low efficiency of the system when integrated with RERs and diverse energy systems. The most commonly used DR program is TOU and RTP pricing to optimize electricity consumption and reduce peak demand. Since the cost of implementing a DR program is less expensive compared to increasing the capabilities of power generation to obtain the peak clipping, a DR program can be adopted to manage the demand and give benefits to both consumers and utilities. Meanwhile, EE measures allow consumers to save energy more efficiently.

To achieve the full potential of DSM activities optimally, the PSO-based method has been reviewed for optimization in various applications and solved the complexity of the models. After many years of development, most of the researchers developed the variants of PSO with the purpose to increase diversity, avoiding premature and enhancing the local search ability, thus improving the quality and robustness of the PSO algorithm. Observations from the study also indicated that improved and hybrid PSO-based models are computationally faster and resulted in better efficiency. The main optimization objectives including minimization of electricity bills, carbon emission, cost operation, peak demand, and discomfort of the occupant have been studied in most of the research works involving different types of consumers considering practical constraints. The proposed PSO-based algorithms proved to be effective in producing substantial cost savings while reducing the peak demand with the integration of the DR program and EE measures. Moreover, the key challenges of implementing PSO in DSM fields were discussed in terms of complexity and uncertainty in optimization, and several suggestions for new applications were identified to give insights for future research. The variants of PSO are used to address the high complexity and uncertainties of the DSM modelling within the acceptable timeframe while considering user comfort.

The application of AI algorithms is very important for the development of various fields in DSM. Therefore, more research on optimization models is necessary, especially when dealing with massive data. The integration of AI with data mining, IoT computing and blockchain, and advanced digital technologies must be combined to enhance the optimization models' performance instead of using them separately. The suggested research areas under DSM to review include the performance of intelligent buildings, smart energy management systems, and the application of demand response in electric power systems. With the increasing intermittent of RERs, the optimization problem of DSM can be more challenging considering the multi-objective function, complex constraints, uncertainties, and many variables. Thus, the enhancement of MA through different strategies such as hybridization, adopting the cooperative approach, and finding optimal parameter settings to deal with the complex problem can be further reviewed as the extension of this study. These applications can be discussed in major classifications of MA, such as evolutionary algorithms, human-based algorithms, physics algorithms, and swarm intelligence. The detailed review can outline the optimal configuration of the MA in solving the high complexity of the DSM optimization problem.

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