Overview of Optimal Energy Management for Nanogrids (End-Users with Renewables and Storage)

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***Abstract*—With the uptake of intermittent renewable generation (namely wind and solar), the battery storage market is now growing and generation in modern power systems is becoming more distributed and behind-the-meter. Utilities are investigating ways to provide incentives to encourage end-users to participate in the overall control of the grid. These developments along with the end-user desire to minimize energy cost, there is a need for automated optimal energy management on the end-user scale. This paper provides an overview of optimal energy management methods suitable for nanogrids. The energy management problem is described for a nanogrid with a grid connection, renewable generation, energy storage, a generator-set, controllable loads and uncontrollable loads. Following, a generalized overview and summary of different techniques for optimal management from a range of literature is presented.**

***Index Terms*—Energy management, nanogrids, energy storage, optimization, renewable energy.**

I. INTRODUCTION

As the penetration of renewable energy resources increases, power grids face new problems primarily related to the intermittency of such resources. For example, in South Australia wind generation currently makes up about 25% (1,473MW) of the state's capacity and 34% (4,226GWh) of the annual generation. Solar PV is installed on 25% of households and this figure is up to 65% in some suburbs. Solar PV provides 11% (663MW) of the total capacity and 7% (857GWh) of the annual generation. In addition, installations of wind farms and solar PV are expected to grow in South Australia. Furthermore 1,505MW of coal and gas generation is being decommissioned leaving less centralized controllability on generation [1], [2]. Similar trends in renewable generation are occurring globally [3].

Utilities are being faced with many new issues with distributed and intermittent generation such as voltage and frequency instability and complicated power flows [4]. Smart grid developments will allow utilities to implement dynamic pricing mechanisms which will encourage end-users to participate in the overall control of networks. Dynamic pricing will bring more stability to modern networks and energy markets and will also allow network operators to make better use of existing infrastructure. In addition, dynamic pricing will provide end-users the opportunity to make savings on energy consumption. Consequently, there is a need for automated optimization on the small scale with the aim of minimizing energy consumption costs.

Therefore, to respond to such changes and highlight the technical research gaps, a review of automated optimization for *nanogrids* is provided in this paper. Since many energy management techniques can be generalized, this review considers studies from a range of contexts including households, microgrids and electric vehicles (EVs). Series hybrid EVs are similar to off-grid generator set-powered nanogrids. One major difference is nanogrids do not have a regenerative load which is a major topic with EVs.

It is also important to highlight that the definitions of some of the terminologies used in the current electricity network are not very clear in the literature, such as macrogrids, microgrids and nanogrids. The terminology, macrogrid is used to represent a traditional grid, which are built around centralized generation and include distribution and transmission networks and numerous customers. A microgrid is a small distribution-level network containing generators, storage and loads, which are built around distributed generation and they have multiple customers. A nanogrid on the other hand is usually a single end-user with embedded generation, storage and loads, which is the context of this study. Examples of nanogrid applications include households, buildings, businesses, campuses, farms, datacenters and hospitals. They may be connected to a network (microgrid or macrogrid) or could be completely autonomous and off-grid. On-grid nanogrids may have the ability to operate autonomously in an islanded mode when the grid supply is lost – enhancing the security of supply for the end-user.

It is important to note here that this review does not consider optimal sizing and design of nanogrids. This paper assumes the nanogrid system exists and focuses on optimal control. Note also that some previous reviews have focused on design of renewable energy systems, including [5] and [6].

Section II in this paper describes the nanogrid level energy management problems. A review of techniques from relevant energy management studies have been summarized and presented in Section III, and conclusions are drawn to highlight the future directions of the research towards optimized energy management in nanogrids.

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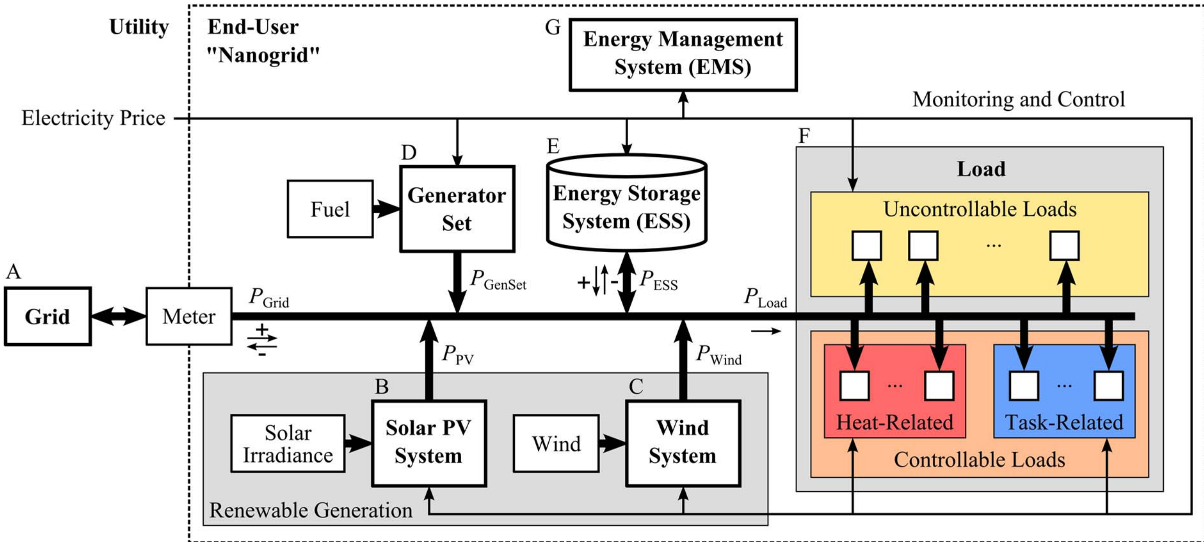

Fig. 1. Generalized Nanogrid – An end-user with a grid connection, embedded generation, storage, various loads and a centralized energy management system

II. Features of Nanogrids

Using common features, component characteristics and operating principles of nanogrids, a generalized block diagram of a nanogrid is given in Figure 1. Table I lists each component and the relevant parameters associated with each. In practice, nanogrids can take on many different forms with any combination of these components. For example, two energy storage systems may be used: one high power unit for supplying transients and voltage support; and another high capacity unit for energy management. The nanogrid could be AC, DC or hybrid, and may also include other forms of generators such as fuel cells. Although this paper considers real power, P only, the discussions towards a modeling approach could be expanded to include reactive power, Q, as well in AC systems. In the following subsections, the major components of the generalized nanogrid are discussed.

A. Grid

The nanogrid may be on-grid (connected to a network) or off-grid. On-grid nanogrids have the opportunity to buy and sell energy to the network. In most cases, the grid can be assumed to be an infinite source or sink of power (resembling a large energy storage device). However, in some cases the rating of the grid connection, P_{Grid_MAX}, may be a limiting factor, especially where there are large loads or in remote areas.

As stated previously, smart grid technologies can allow utilities to implement dynamic pricing mechanisms. This can also encourage better use of network infrastructure and give utilities a form of control in networks where generation is becoming more distributed, while giving customers opportunities to make savings. Network operators may also offer incentives to end-users to provide voltage and frequency support and assistance in black start situations. Therefore, it is important to consider an overview of different pricing schemes which may be implemented by utilities.

1) Pricing of Energy Consumption

Utilities can provide customers with different pricing schemes to buy (C_{Buy}) and sell (C_{Sell}) energy in \$/kWh. Utilities may also have pricing schemes for reactive power.

Fixed pricing is where the electricity price is constant. This is the traditional form of pricing for households and small business. Some utilities implement different tiers where the price per kWh increases as consumption increases (related to peak pricing). Time of Use Pricing (ToUP) is where there are different fixed prices for fixed periods of the day (or year). These are usually called on-peak and off-peak times. Critical Peak Pricing (CPP) is where utilities increase the price to discourage usage and avoid a blackout on days when demand

TABLE I. Typical Parameters of Nanogrid Energy Management Control

Component	Parameters to observe	Parameters to control	Specifications
A Grid	C_{Buy} Buy Price (\$/kWh) C_{Sell} Sell price (\$/kWh)	P_{Grid} (+/–) (kW)	P_{Grid_MAX} Rated Power (kW)
B Solar PV System	P_{PV} (kW)	Limit Output Power (kW)	Rated Power (kW)
C Wind System	P_{Wind} (kW)	Limit Output Power (kW)	Rated Power (kW)
D Generator Set	C_{Fuel} Fuel Price (\$/L) V_{Fuel} Fuel available (L)	P_{GenSet} (kW)	P_{GenSet_Rated} Rated Power (kW) $T_{StartTime}$ (s)
E ESS	E_{ESS} Stored Energy (kWh) SoC State of Charge(%)	P_{ESS} (+/–) (kW)	P_{ESS_MAX} Power Rating (kW) E_{ESS_MAX} Energy Capacity (kWh) η_{ESS} Round Trip Efficiency (%)
F Load	P_{L1}, P_{L2}, … , P_{LN} (kW) Controllable Load Requests and Parameters	Controllable Loads • On/Off Control • Power Control (kW)	Rated power On time/Duty cycle/Load profiles Starting power/Transients

is suspected to reach the grid limits. Real-Time Pricing (RTP) is where prices are announced to customers in real-time, at regular intervals and stay constant for the interval. Typical intervals are five minutes or one hour. In some energy markets RTP can go negative when there is excess generation. RTP is a stochastic process.

2) Pricing for Peak Demand

Utilities may also charge customers based on peak, because the network operator needs the infrastructure to supply the peak demand. The simplest is the customer having an agreement with the utility to not exceed a certain peak. Another form is having separate charges for energy consumption and peak demand (in $/kW) [7]. A third form is determining consumption pricing based on peak demand tiers.

B. Solar PV System

As it is known, the output power, P_{PV}, in a solar PV system is dependent on the solar irradiance which is affected by the path of the sun in the sky, the angle of the panels, atmosphere, rain, cloud cover and obstructions. Hence P_{PV} is a stochastic process and the only control available is curtailment.

C. Wind System

A wind generator system contains a wind turbine connected to a generator followed by a converter. Although prediction studies are presented in the literature, the output power, P_{Wind}, is also a stochastic process because it is dependent on wind velocity, turbulence, humidity and temperature [7].

D. Generator Set

A generator set has a rated output power, a fuel tank or supply, start-up time and efficiency versus loading characteristic. Fuel has a price per volume and is typically paid in advanced – with the exception of gas generator sets connected to a supply line. Figure 2 illustrates a typical fuel consumption curve for a diesel generator [8]. Generator sets are most efficient when operated at rated power. In systems supplied by only a generator, the demand is often low and the generator set is left idling most of the time. The "governor" in a generator set controls the fuel to maintain constant speed under different loading conditions, meaning the generator is internally controlled to match demand [9]. P_{GenSet} can be manipulated by adjusting the controllable loads and energy storage.

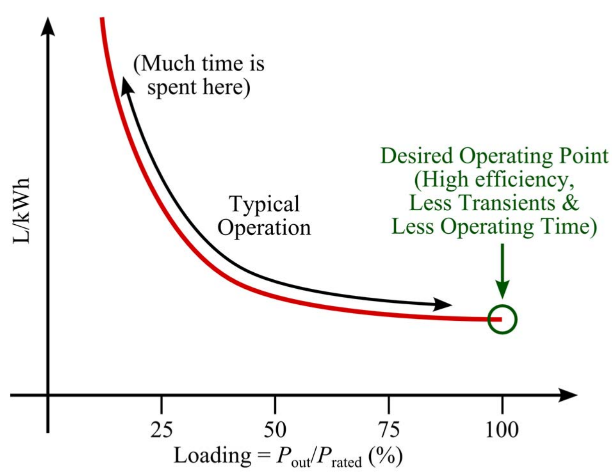

Fig. 2. A typical diesel generator consumption curve highlighting typical operation and desired operation

Kusakana and Vermaak [10] investigate the advantages of adding battery storage to a diesel generator in an off-grid system. The batteries supply the load and the diesel generator charges the batteries. This decoupling allows the diesel generator to operate at maximum efficiency and for shorter time, reducing fuel, refueling, maintenance and replacement costs.

E. Energy Storage System (ESS)

The ESS is able to supply and store energy on demand, depending on limits. The ESS has a storage capacity, E_{ESS_MAX}, and a power rating, P_{ESS_MAX}. It has charge and discharge efficiencies and self-discharge characteristics [11]. Equations (1-3) represent the model and constraints of an ESS [12]. Notice the time-coupling attribute in (3). This makes real-time optimization complex because current decisions will affect future situations. In addition, aging parameters can also be included in ESS modeling.

$$0 \le E_{ESS}[t] \le E_{ESS\_MAX} \tag{1}$$

$$-P_{ESSchMAX} \le P_S[t] \le P_{ESSdisMAX} \tag{2}$$

$$E_{ESS}[t+1] = E_{ESS}[t] + (P_{ESS}^{-}[t].\eta_{ESSch} - P_S^{+}[t]/\eta_{ESSdis})\Delta t \tag{3}$$

A unique form of ESS in nanogrids could be parked EVs, which is investigated in [13] for grid connected storage.

F. Load

The load is another largely stochastic process. Loads may be uncontrollable or controllable to varying degrees. Uncontrollable loads, such as lighting and computers, require power on demand. In the near future smart appliances may be controllable and allow for more energy management opportunities. Publically available load profiles of common household appliances are provided and their controllability are discussed in [14]. Controllable residential loads are modeled in [15]. In [12], Wu *et al.* categorize controllable loads into heat-related and task-related loads. Heat-related loads are thermostatically controlled and include electric hot water heaters as well as air conditioners. Task-related loads have a start and stop time, can be interrupted and require a specified amount of energy. Examples include clothes dryers and electric vehicle chargers. It must be noted that interrupting some loads often may not be beneficial, especially if they have a surge start (e.g. motor driven loads). Table II provides a summary of common loads in a nanogrid.

TABLE II. COMMON CONTROLLABLE LOADS

Uncontrollable Loads		Lighting, Computer, TV, microwave, refrigerator, oven, stove, kettle
Controllable Loads	**Heat-Related**	Electric Water Heater (EWH), Air-Conditioner (AC)
	Task-Related	Clothes Dryer (CD), Electric Vehicle (EV), Pool Pump

G. Energy Management System (EMS)

The EMS is a centralized controller that monitors and controls the generation, storage and loads and performs optimization. Weather forecasts have proven useful for learning and prediction of solar, wind as well as load [16]. Other data that may be utilized in control include: historic load and generation data; time; day of week; and day of year. Ideally the energy management algorithm should learn and adapt since nanogrids take many different forms and are likely to change over time.

It should be noted that energy management does not have to be performed by a centralized controller. The control can be distributed. Lagrose *et al.* [17] present a multiagent energy management system, where each DC-DC converter is an agent. These agents operate autonomously and communicate to a "blackboard" for sharing information.

H. Nanogrid Operating Principles

1) Equations

The operation of the nanogrid operation can be described using basic equations. For example, the power in the system must always be balanced as in

$$P_{PV} + P_{Wind} + P_{GenSet} + P_{Grid} + P_{ESS} = P_{Load} \quad (4)$$

Power difference, ΔP, can be defined as

$$\Delta P = P_{REN} - P_{Load} \quad (5)$$

where P_{REN} is the total renewable generation ($P_{PV} + P_{Wind}$). In the case of deficit ($\Delta P<0$), power must be sourced from the grid, ESS or generator or controllable loads can be turned off. Conversely, in the case of surplus ($\Delta P>0$), the excess renewable generation can be used to charge the ESS, be exported to the grid, controllable loads can be turned on or the renewable generators can be curtailed.

The combined cost of grid energy consumption under real time pricing (RTP) and fuel usage over a time period is given by (6).

$$Cost = \sum \left(E^{+}_{GRID}[t] \times C_{Buy}[t] - \sum E^{-}_{GRID}[t] \times C_{Sell}[t] + V_{Fuel\_used} \times C_{Fuel} \right) \quad (6)$$

Here, E^{+}_{GRID} is the energy bought from the grid and E^{-}_{GRID} is the energy sold to the grid.

2) Base Case

The *base case* control method is a naïve greedy algorithm as described in Algorithm 1. It provides a benchmark for energy management algorithms to be compared. The base case does not take advantage of dynamic pricing mechanisms nor does it consider controllable loads. A similar control is described as "balancing/greedy control" under constant price in [11].

Algorithm 1 – Base Case

```
For each time slot t:
    All renewable power is supplied to load
    IF (ΔP>0)      // Surplus
        IF (SoC<100%)
            P_ESS = –min(ΔP, P_ESS_MAX)  // Charge ESS
        P_Grid = –(ΔP – P_ESS)       // Sell excess to Grid
    ELSE           // Deficit
        IF (SoC>0%)
            P_ESS = min(–ΔP, P_ESS_MAX)  // Discharge ESS
        IF (insufficient P_ESS OR SoC)
            P_Grid = –(ΔP + P_ESS)  // Source from Grid
            IF (insufficient P_Grid)
                Use Generator
```

3) Objectives

There are many objectives an energy management algorithm can target. Common examples of energy and power objectives are listed in Table III. The main objective most end-users will require is overall long term cost minimization as in

$$\min_{P_{ESS}[t], P_{GenSet}[t], P_{ControlLoad}[t]} \lim_{T\to\infty} \sum_{t=0}^{T} cost[t] \quad (7)$$

This may incorporate some or all of the others as sub-objectives. Minimizing peak demand is desirable for customers where pricing schemes incorporate penalties for peak demand. Minimizing emissions would be desirable where there are taxes on emissions. Minimizing fuel usage would be desirable where security of supply is an issue, especially in remote locations. Batteries are expensive and hence maximizing their life is desirable.

Since renewable generation, RTP and load are stochastic processes, it is challenging to perform optimization in real-time. The ideal case or set of cases can be found offline and used to measure how effective a real-time algorithm performs with respect to other algorithms and the base case.

TABLE III. ENERGY MANAGEMENT OBJECTIVES

Energy	Power
• Minimize Cost • Maximize Overall Efficiency • Minimize Peak Demand • Minimize Emissions • Minimize Fuel Usage • Maximize ESS Life • Maximize Generator Life • Maximize Reliability and Security of Supply • (Others…)	• Provide Frequency Support • Provide Voltage Support • Increase Inertia • (Others…)

III. REVIEW OF TECHNIQUES USED IN ENERGY MANAGEMENT

A range of techniques have been applied in optimal energy management studies. Table IV provides a summary of the techniques reviewed in this section. Figure 3 illustrates three different techniques used in energy management control.

TABLE IV. TECHNIQUES USED FOR ENERGY MANAGEMENT

Technique	References
Fuzzy Logic Control (FLC)	[12], [16], [18], [19], [17]
Linear Programming (LP) and Integer Programming (IP)	[12], [20]
Dynamic Programming (DP)	[11], [21]
Lyapunov Optimization (LO)	[22], [23], [24]
Neural Networks (NN)	[25], [16], [26], [27], [19]
Genetic Algorithms (GA)	[28], [26], [25]
Markov Decision Process (MDP)	[29], [21], [30], [31]

A. Fuzzy Logic Control (FLC)

FLC is a control technique that is based on linguistic logical rules such as "IF *SoC* is low AND *RTP* is low THEN charge ESS high". FLC is not an optimization technique by itself; however FLC can make more intelligent decisions than the base case (e.g. take advantage of low prices).

FLC has been applied in a wide range of energy management studies and often combined with other techniques. Wu *et al.* in [12] present a fuzzy logic control based algorithm for a household with PV, an ESS and controllable loads. In [17] a multiagent energy management study is presented with PV generation, two batteries, two fuel cells, a super-capacitor and load. The battery agents use FLC with the battery *SoC* and super-capacitor *SoC* as inputs. The battery agents have three goals: 1. Charge when *SoC* is low and super-capacitor *SoC* is high (i.e. high DC bus voltage); 2. Discharge when *SoC* is high and super-capacitor *SoC* is low; and 3. Avoid deep discharge. However, when the super-capacitor has a *SoC* of one and the battery *SoC* is less than one, the FLC is overridden with a maximum charge calculation that takes ΔP into account. Mohamed *et al.* in [18] used FLC only when there is a power deficit to control the discharge power of the battery. Chaouachi *et al.* [16] used a FLC based scheduler for battery scheduling in microgrids.

B. Linear Programming (LP) and Integer Programming (IP)

LP and IP are optimization techniques for systems of linear inequalities. They involve defining a feasible region which is used to find the optimal solution. In LP, intersection points (vertices of the feasible region) are tested for the optimal solution. IP is more difficult to solve because the integer constraint requires all points in the feasible region to be iterated through to find the optimal solution. Mixed integer linear programming (MILP) is a hybrid form with both continuous and integer variables. MILP is utilized in [20] and [12]. Relaxation of integer programming refers to relaxing the integer constraints to continuous constraints hence making the problem solvable by LP at the cost of no guarantee of finding the truly optimal solution. Wu *et al.* [12] applied a relaxation based energy management algorithm. Compared to the MILP based management the computational time was greatly reduced and there was only a small increase in overall cost. In the same paper FLC has a much faster computational time but the cost reduction is not as great. However the MILP and relaxation optimization approaches rely on predicted values of the stochastic processes whereas the FLC method does not [12].

C. Dynamic Programming (DP)

A number of studies present optimal energy management methods based on DP. Harsha and Dahleh [11] presented an optimal management based on DP for renewable energy, storage and dynamic pricing. Löhndorf and Minner [21] used dynamic programming with MDP for day-ahead trading of renewables.

D. Lyapunov Optimization (LO)

LO has been used in a number of energy management studies. LO has the advantage of not requiring future values or statistics of the stochastic processes. Results are within the order of "O(1/V)" of the ideal case where V is related to ESS capacity.

Urgaonkar *et al.* used LO to minimize cost the RTP consumption cost of a data center utilizing UPS as energy storage [22]. In [23], Guo *et al.* presented an optimal energy management technique based on LO for households with renewable generation and storage under RTP. They studied cases for uncontrollable loads and controllable loads. Huang, *et al.* [24] applied LO for adaptive scheduling in a microgrid with multiple residential customers.

E. Neural Networks (NN)

NN have been used for prediction and control in optimal energy management. NN have the advantage of being adaptive (with reinforcement learning NN) and being able to learn complex models that are difficult to determine otherwise. The downside to NN is they need to be trained. Matallanas *et al.* [25] presented a scheduler and coordinator based on Multilayer Perceptron NN (MLPNN) for a household with PV, ESS and deferrable loads. Shahgoshtasbi and Jamshidi [19] used NN for household energy management. In [16] Chaouachi *et al.* used a NN ensemble (NNE) consisting of three different NNs for forecasting solar generation, wind generation and load demand in a microgrid. They compared the three individual NN with the NNE for verification: MLPNN; Radial Basis Function (RBFNN); and Recurrent neural networks (RNN). Chen *et al.* [26] also used NN for forecasting PV generation in a microgrid. Mellit and Pavan presented and demonstrated a solar irradiance forecaster based on NN as well [32]. Finally Moren *et al.* [27] presented NN based energy management system for a series hybrid EV.

F. Genetic Algorithms (GA)

GA are iterative optimization algorithms inspired by natural selection. Dufo-López and Bernal-Agustín [28] present an energy management design and control strategy based on GA. Chen *et al.* [26] use GA for energy management control. Matallanas *et al.* [25] use GA to adjust and train MLPNN controllers.

G. Markov Decision Process (MDP)

The MDP is a formulation of states, actions and rewards for control and optimization problems with stochastic

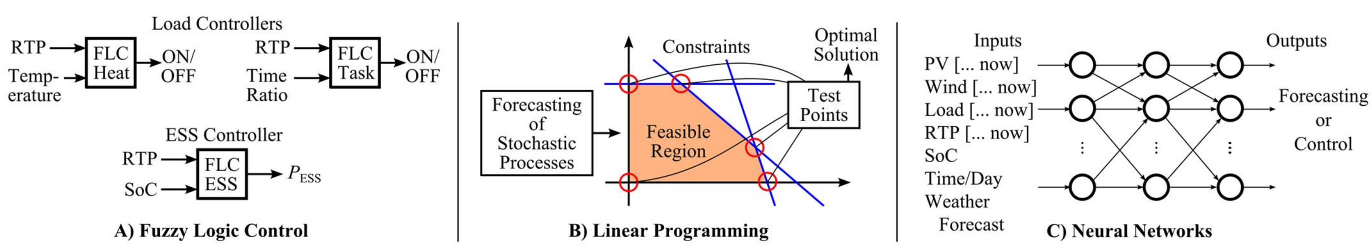

Fig. 3. Illustration of three different techniques used in energy management

processes. Once the MDP is set up optimization can be performed with techniques such as LP and DP. Vivekananthan, *et al.* in [29] and Kim and Poor in [30] utilized MDP for scheduling loads to reduce energy cost under RTP. Van de Ven *et al.* [31] applied the MDP with dynamic programming for controlling end-user storage to take advantage of dynamic pricing.

IV. Conclusion

Real-time optimal energy management for end-users is a complex problem due to the stochastic nature of intermittent generation, loads and RTP along with different system configurations. There are a range of techniques that can be used to approach this problem. These come from a variety of areas including control, mathematical optimization and artificial intelligence. With these techniques there is often a tradeoff between computational complexity and performance (how close the result is to the ideal case).

Many of the studies reviewed have not considered all the components of the nanogrid presented in Section II. For example, studies [29] and [30] consider scheduling loads and do not consider embedded generation and storage. Hence future work to develop an improved energy management algorithm for nanogrids, may involve combining and generalizing these techniques. Furthermore side-by-side comparisons of different techniques also have not been studied thoroughly. Wu *et al.* in [12] have made some progress in this area by comparing FLC, MILP and linear programming relaxation. However, these techniques have not been compared to others such as LO and NN control.

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