Balancing between Demand and Trading in Microgrids

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Abstract— **The envisaged future generation power or smart grid (SG) will incorporate ICT technologies as well as innovative ideas for advanced integrated and automated power systems. The bidirectional information and energy flows within the envisaged advanced SG together with other aiding devices and objects, promote a new vision to energy supply and demand response. Meanwhile, the gradual shift to the next generation fully fledged SGs will be preceded by individual isolated microgrids voluntarily collaborating in the managing of all the available energy resources within their control to optimally serve both demand and distribution. In so doing, innovative applications will emerge that will bring numerous benefits as well as challenges in the SG. This paper introduces a power management approach that is geared towards optimizing power distribution, trading, as well as storage among cooperative microgrids (MGs). The initial task is to formulate the problem as a convex optimization problem and ultimately decompose it into a formulation that jointly considers user utility as well as factors such as MG load variance and associated transmission costs. It is deduced from obtained analytical results that the formulated generic optimization algorithm characterizing both aggregated demand and response from the cooperative microgrids assist greatly in determining the required resources hence enabling operational cost viability of the entire system.**

Keywords— energy cooperative microgrids, energy storage system, smart grid

I. Introduction

As the existing electrical power system infrastructures are fast approaching their rated capacities, next generation SGs become a viable alternative as well as ultimate solution. The key components of an SG, such as advanced metering infrastructure (AMI) and renewable energy generating resources, have resulted in a demand for the devising of new grid management approaches. Typically, the bidirectional operation of next generation SGs as well as high renewable energy integration has the potential to enhance the overall stability of the grid in terms of demand and supply. Renewable energy integration implies sporadic injection of renewable energy resources into the existing power grid and this will certainly complicate the overall energy management. This is partly because renewable energy sources produce output power (peak) in unpredictable ways as wind or sunlight strengths will vary from time to time, thus making it difficult for any network operator to rely on them for balancing supply and demand. Overall, various issues related to the integrating of the renewerable resources into a grid emerge. These include voltage stability, power factor quality, harmonics, devices protection and overall power grid system reliability. With regards to voltage stability, it is generally noted that as the number of distributed generations increase, so will be the number and capacities of energy storage systems (ESSs). The latter has the potential to reduce the uncertainty as well as fluctuations associated with distributed generation and thus the rated grid's voltage/frequency profiles can be stabilized. However, on-lining of a single distributed generator may immediately trigger localized load, voltage, frequency control as well as demand response.

It is also necessary that all SG devices be monitored in real time. hence the necessitation of advanced information and communications technology (ICT) subsystem infrastructures to facilitate reliable connectivity as well as secured connectivity. In this case, the efficiency as well as both physical and semantic security of the ICT subsystem are imperative. It is generally agreed that computational efficiency in the energy management of an SG is key to its successful operation.

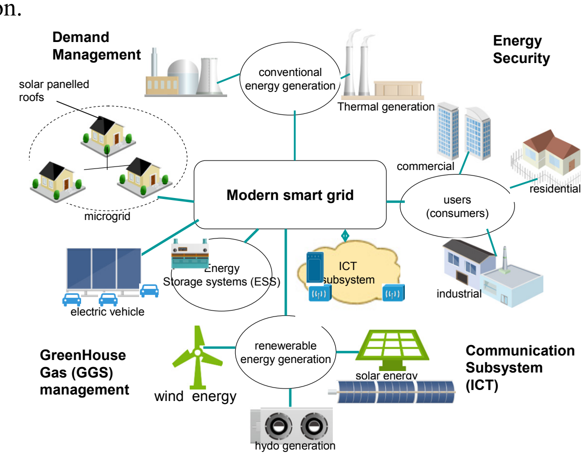

Fig. 1. Key SG components.

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A typical SG and its components are illustrated in Fig. 1. It basically comprises smart power and ICT subsystems. By smart power system, this refers to a reliable as well as an intelligent power system which comprises distributed power generation, transmission, distribution, as well as storage (ESSs). The ICT subsystem facilitates advanced metering, smart monitoring, and the corresponding information management. The ICT subsystem will also facilitate the implementation of key SG applications relating to energy management, system reliability, security and privacy. Other emerging applications include energy management for large-scale support of electric vehicles (EV) and distributed generation of renewable energy in MGs.

Overall, key to the successful operation of SG (or at MG level), is the implementation of demand-side management [1] [2]. The inclusion of renewerable generation means information regarding demand and generation comes from a variety of sources sparsely located within the SG, and at multiple timescales. This same information will be used to shift peak load and peak hours utilizing distributed optimization, as well as ultimately preventing peak loading on the SG system. Individual users are also able to embark on their own home demand side energy management by shifting electricity consumption of high energy usage appliances to off-peak hours. Smart enabled user appliances could be selectively put off during peak hour demand as well as concurrently execute intelligent strategies to shift energy consumption to non-peak hours [3].

In [4], the authors analyzed a game theory-based power consumption scheduling model for individual user (residential) energy management. By assuming customers were selfish and self-interested, the authors examined a distributed algorithm for solving the game model via the best response dynamics, which enables information exchange amongst all residential customers to reduce the peak-to-average ratio (PAR). However, customers may be discomforted by load shifting, whereas minimization of billing cost and PAR are the focus in [5]. These approaches are considered as the traditional techniques. Overall, the smart grid approach is bringing in a new scenario with regards to generation, distribution and consumption in which various disciplines such as physical sciences, computer science, telecommunications, and power engineering are called upon to try to resolve new related problems. Because the smart concept offers a new approach to energy demand, generation and control, we thus in this paper explore synergies between energy generation and using optimization techniques so as to reduce operational expenditure (OPEX) as well as capital expenditure (CAPEX) costs. The optimization approach provides key support tools for monitoring energy usage and reducing its derived costs, precise determination of renewable distributed generation (RDG) demands in view of improving system sustainability, and lastly future planning of the network as well as new RDG systems. In particular, this paper will focus on addressing allocation issues under the context of cooperating microgrids as we evolve towards fully fledged smart grids.

II. RELATED WORKS

In a bid to reduce adverse environmental effects as well as CAPEX/OPEX costs associated with fossils-based power generation systems, communities living within a locality can interconnect their various types of individually owned distributed energy generators resulting in a MG formation. Key to the optimal power demand and supply in that MG would be in its capability to provide the power to all households within its vicinity as and when required. However, because of the intermittent nature of renewable power generation, often some neighboring MGs would have excess generation as well as storage capacities than others. It is therefore worthwhile for neighboring MGs to operate in a cooperative manner by interconnecting and sharing the available power and generating/storage resources.

As a result of the cooperative association between the MGs, the problem of residential demand-side management arises. This is because the cooperative MGs ought to optimally operate to the satisfaction of all participating users. The resulting residential demand-side management problem can thus be modeled as having sparse constraints that are focused on relieving users' discomfort from load shifting or interrupting.

It is also necessary to address an appropriate trading model for microgrid operations, where a risk-free optimal trading strategy can be devised as well as optimization of resources taking into consideration the uncertainties of power generation levels from time to time.

Lots of past and current research work has focused on the energy trading problem in cooperative MGs. The traditional power and similar will always be prepared to be included in the energy trading market. Further advancements in renewerable technology [6] have provided an impetus for creating MGs with affordable multiple distributed energy conversions. Since demand and generation problem arises from a multitude of sources and at various timescales in MG-based energy trading markets, new distributed optimization and control solution approaches as well as technologies are necessary to further reduce OPEX as well as CAPEX, thus ultimately driving towards more economical and environmental benefits with regards to next generation smart grids. These approaches and technologies pose the potential to bring about a reduction in the intermittency of renewable energy by way of implementing various reactive preventive demand response programs. The authors in [8] studied a distributed optimization framework for the energy trading amongst islanded MGs. A game theory-based energy consumption scheduling model for residential energy management in smart grids was proposed and analyzed in [7]. In this same work, the authors examine a distributed algorithm for solving the model via the best response dynamics, which enables data exchanges amongst all users in a bid to lower the peak-to-average ratio [9]. A linear supply bidding function-based demand response program is proposed in [10] whereby an operator collects the bids and capacities from each user and utilizes them to achieve some form of competitive equilibrium. In [11] and [12] the researchers proposed and analyzed a multi-layer energy trading market for electric vehicles in which the trading price and the quantity of the energy to trade was determined using some form of a proposed double auction mechanism. In all the works mentioned herein, the general intermittency of renewable energy coupled with demand uncertainties were never considered. The two exposes the system's reliability to vulnerability. Therefore, it may be necessary to use both stochastic and probabilistic measures to solve the problem as it is random in nature. The authors in [13] introduced a dynamical model with certain probabilistic transitions which can be played by one or more players. The proposed energy trading model incorporates the day-ahead as well as real-time markets.

This paper explores real-time energy demand and the supply management problem for cooperative MGs. It is assumed in this paper that each individual macrogrid controller (MC) intends to serve its users with full satisfaction, as well as sustainability of the available RDG systems. Each MC may consist of several RDG as well as a centralized ESS system. Power demand and supply within each MC is coordinated as well as facilitated by a dedicated in-house MG control center (MGCC). An external control center (MaGCC) coordinates both power exchanges between the two cooperative MCs as well as power trading.

III. USER POWER USAGE MODELLING

Considered is a system of cooperative MGs which trade as well as exchange power via a commonly shared power bus.

A. Optimization at Consumer Level

It is also assumed that a standard user N , $n \in \{1,...,N\}$ household appliances. Their power usages are modeled over a 24 hour period. By introducing a power usage matrix, $[A_n]$ defined by R_n rows representing load curves and corresponding T (one hour time intervals) characterizing $n \in \{1,...,N\}$. The defined matrix can be used to determine power usage at any arbitrary time t as being equal to:

$$a(t) = \sum_{n=1}^{N} a_n^{\alpha_n}(t) \tag{1}$$

where $a_n^{\alpha}(t)$ as an element of $[A_n]$, a row $\alpha \in [1,...R_n]$ and corresponding column $t \in [1,...T]$.

Next, it is also necessary to elaborate further on factors such as cost benefit as well as power generation costs linked to the user's $n \in \{1,...,N\}$ appliances.

If the user owns a total of M , $n \in \{1,...,M\}$ RDG sources, then the corresponding aggregated generation capacity is:

$$g(t) = \sum_{n=1}^{M} g_n(t) \tag{2}$$

g(t) comprises a fraction that is utilized in house $g^I(t)$ and the traded component $g^E(t)$.

Consequently, the corresponding cost of generating the power to support the $n \in \{1,...,N\}$ appliances is:

$$aC(t) = \sum_{n=1}^{M} c_n(g_n(t)) \tag{3}$$

Considering equations (1), (2) and (3) and objective function characterizing the user's power usage is expressed as:

$$\begin{aligned} f = & \sum_{n=1}^{N} d_n^{\alpha_n} - \sum_{t=1}^{T} p_a(.)\left[\sum_{n=1}^{N} a_n^{\alpha_n}(t) - g^I(t)\right] \\ & + \sum_{t=1}^{T} p_g(.) \times g^E(t) - \sum_{n=1}^{M} c_n(g_n(t)) \end{aligned} \tag{5}$$

where d_n^{α} is a cash equivalent benefit and $c_n(g_n)$ - is a unit cost of generating power.

The ultimate objective is to ensure that there is always more power traded to the grid:

$$g^E(t) \le g(t) = \sum_{n=1}^{M} g_n^{(t)} \tag{6}$$

From (5) it also follows that for a user trading all his/her own generated power by, i.e. $g^E(t) = g(t)$ we have;

$$f = \sum_{n=1}^{N} \sum_{t=1}^{T} \left[\frac{d_n^{\alpha_n}}{T} - p(t) a_n^{\alpha_n(t)} \right] + \sum_{n=1}^{M} \sum_{t=1}^{T} \left[p_g(t) \times g_n(t) - c_n(g_n(t)) \right] \tag{7}$$

Our objective would be to maximize;

$$f = \sum_{n=1}^{M} \sum_{t=1}^{T} \left[p_g(t) \times g_n(t) - c_n(g_n(t)) \right] \tag{7}$$

IV. POWER SCHEDULING BETWEEN MGs

Fig. 2 illustrates an example of power storage sharing among cooperative MGs. As illustrated, three MGs have their individual ESSs interconnected. It is assumed that power charging to ESS_i is $C_i \ge 0$ (with charging efficiency $0 \le \eta_i^c < 1$). Similarly for discharging is $D_i \ge 0$, and discharging efficiency is $0 \le \eta_i^d < 1$.

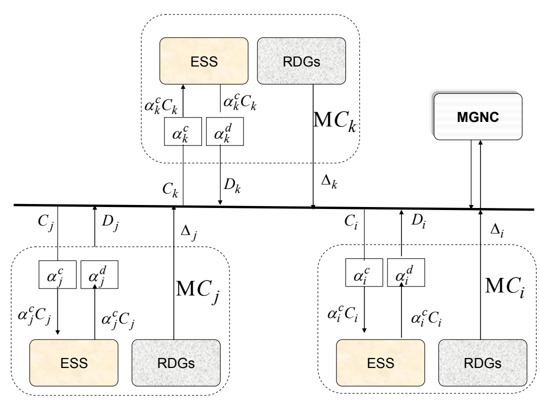

Fig. 2. Energy transfer model of system

The storage capacity of ESS_i is;

$$S_i = S_i + \eta_i^c C_i - \frac{D_i}{\eta_i^d} \tag{8}$$

$$f = s_{i,\min} = s_{i_i} + \eta_i^c \sum_{k=1}^{i} C_i - \frac{1}{\eta_i^d} \sum_{k=1}^{i} D_i \le s_{i,\max} \quad (9)$$

The constraint on the power level storage levels would be given by:

$$s_i'(t) = s_i(t) - \xi \;;\; s_i(t-1) \quad (10)$$

$$s_{i,\min} \le s_i(t) \le s_{i,\max} \;,\; \forall\; i \in i,j,k \quad (11)$$

$$\frac{s_{m,\min}}{(1-\xi)} - s_{m,\max} \le s_m'(t) \le s_{m,\max} - s_{m,\min} \quad (12)$$

V. LOAD PREDICTIONS

To further enhance the demand and supply optimization among cooperative MGs, load predictions may be done with the aid on a neural network (NN) set. In this case, we forecast tomorrow's load (load T) by using load demand curves obtained an hour earlier, (T-1), day before (T-24) and one week ago (T-168). [14], [15]. The next day load forecasting is then conducted hour by hour. The next hour forecasting is based on the prediction of previous one. The authors in [14] also incorporated various factors that could affect power generation and usage. These included weathers, season, as well as economic factors [14]. Under weather factors, element such as temperature humidity index (THI), dry bulb temperature (DBT), wind chill index (WCI) and wet bulb temperature (WBT) are considered.

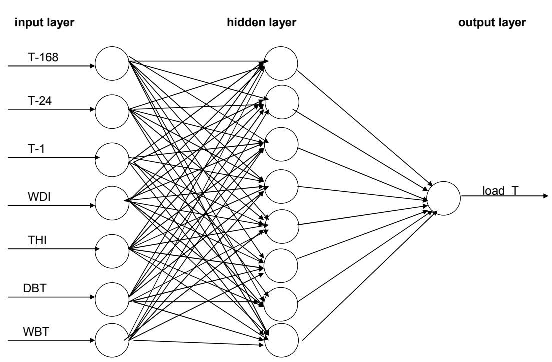

Fig. 3. Tomorrow's load forecasting using NNs

The advantage in the use of artificial NNs (ANNs) in load forecasting is in that it does not require assumption of any direct mappings between load and climatic variables in the necessary non-linear modeling and adaptation associated with the load prediction process. The next day load is determined by way of iterative forecasting method explained in [16]. As shown in Fig. 3, the ANN network comprises three layers; input, hidden (middle) as well as the output layer. The hidden layer is key in ensuring the balance of model flexibility as well as over-fitting. A sigmoid function is used for activation.

VI. ANALYSIS

We first compare two ESS charging approaches namely:

- Linear Supply Function Based Pricing, which relates to a linear supply function-based pricing method is applied to dynamically adjust the charging strategy according to the different levels of the charging.
- Charging Strategy by Stochastic Game, where in this case, the additional charging load may affect the lifespan or failure of the charging transformer hence that risk is considered.

In this section, we evaluate the two-stage stochastic game approach on the energy management studied. The data used for the analysis is obtained from both [17] and [18]. Key climatic data such as solar intensities, wind availability speed, humidity and daily average temperatures are also derived from the same sources. The data is normalized over a 24-hour period, i.e. corresponding to a full day with hourly intervals $\Delta t = 1$ for case study purposes.

Table 1. Parameters of a typical CHP system

No	Parameters			
	DR	$Q_{\max}$	UR	η
1	680	1300	680	45
2	680	1288	680	45

** DR, $Q_{\max}$ and UR are measured in kWh

The predictive excess power output of 4 MGs: namely, CHP, wind, PV and DR based is provided in Fig. 4. It is noted that the wind in the areas chosen has a relatively greater degree of fluctuations as well as uncertainty.

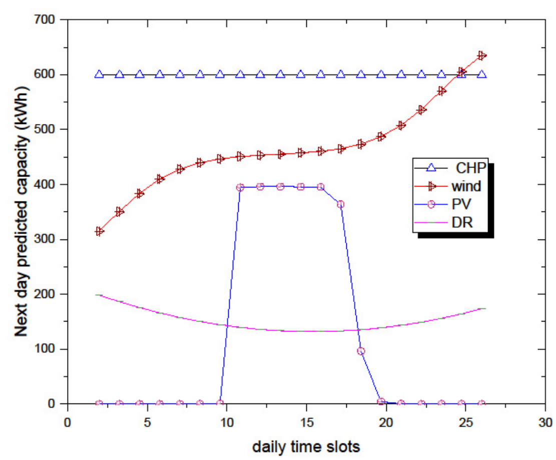

Figure 4. Predictive power output for 4 MGs

We further go on to explore an optimal ESS storage capacity required for each MG. Each MG charges its ESS when available grid power is priced lowest and discharges when the cost escalates. Each charge controller is rated at approximately 20% of the ESS capacity in (Ahs). In practice, the charging will take much longer because of the excessive losses (typically up to 40%) involved.

Table 2. System Specifications

ESS		Grid Line Ratings	
η_i^c	0.9		
η_i^d	0.9	R(type I)	$0.1\ 1\Omega / km$
S_i	0	R(type II)	$0.3\ \Omega / km$
$S_i^{\min}$	0	d	$50km$
$S_i^{\max}$	80MW	V	$33kV$
$S_j^{\max}$	100MW	E	$50MW$
$S_k^{\max}$	*115 MW*	T^o	$0^o - 27^o$ *max*

Provided in Table 2 are the key electrical specifications of the ESS system as well as key power grid transmission line parameters.

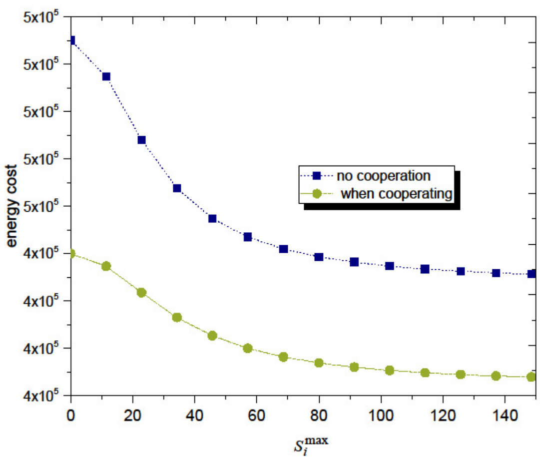

Fig. 5. Power cost versus required ESS capacity.

An analytical plot of the total power cost versus the available ESS in the MGs is provided in Fig. 5 in which it is ascertained that total energy cost is achieved with a relatively lower value of $S_i^{\max}$.

VII. CONCLUSION

In this paper, we looked at energy management for cooperative MGs. We formulated the user energy management problem as a practical optimization problem to minimize the total system cost including those of the MGs, The initial task was to formulate the problem as a convex optimization problem and ultimately decompose it into a formulation that jointly takes into account user utility as well as factors such as MG load variance and associated transmission costs. It is deduced from obtained analytical results that the formulated generic optimization algorithm characterizing both aggregated demand and response from the cooperative MGs assist greatly in the determination of optimal resources (in terms of quantity) to enable operational cost viability of the entire system

This work can be further extended in two directions. First, we will consider the intermittency of renewable generation and demand, for which the current deterministic methods are no longer applicable. Secondly, we will investigate the detailed internal trading mechanism such as how to control the pricing in the available supporting SG grid network to encourage the energy sharing among different MGs.

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