Wolf Pack Hunting Strategy for Islanded Micro-Grid

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Abstract— The interest on micro-grid has increased significantly triggered by the increasing demand of reliable, secure, efficient, clean, and sustainable electricity. More research and implementation of micro-grid will be conducted in order to improve the maturity of micro-grid technology. Among different aspect s of micro-grid, this paper focuses on the conventional centralized automatic generation control (AGC) is inadequate to handle the ever-increasing penetration of renewable energy and the requirement of plug-and-play of smart grid, since a mixed homogeneous and heterogeneous multi-agent based wolf pack hunting (WPH)strategy to achieve a fast AGC power dispatch, optimal coordinated control, and electric power autonomy of an islanding smart distribution network (ISDN).Simulation results demonstrate that WPH has a greater robustness and a faster dynamic optimization than that of conventional approaches, which can increase the utilization rate of the renewable energy and effectively resolve the coordination and electric power autonomy of ISDN.

Key words: Automatic Generation Control, Islanding Smart Distribution Network, Wolf Pack Hunting

I. INTRODUCTION

The limited generation in the power sector has continually been exacerbated by load growth, power demand, limitations in the ability to site new transmission lines, limitations in the ability to construct large scale generation due to increased environmental regulation, and lack of technology development to meet the new requirements. Manpower is required to achieve the development of a sustainable, secured, and economically-viable society and infrastructure. The growth in developed and developing countries has created an energy divide in terms of wealth. The major disparities of energy consumption per capita are reflected in developing countries. The universal electrification challenge to meet the world's population growth in order to attain its current per capita electricity consumption will require massive increase in electricity generation capacities. A higher randomness and uncertainty of the active power and load disturbance of smart distribution network (DN) will be resulted in by the ever-increasing penetration of distributed generations and active load integration. Consequently, a massive information gathering and high computational burden will be emerged in the energy management system (EMS) [1, 2], which brings in many new problems and challenges to automatic generation control (AGC) of islanding DN (IDN). As a result, it is necessary to study the multi-agent system (MAS) decentralized coordinated control of AGC for IDN. AGC can be normally divided into two procedures: (a) The total power references tracking of AGC, and (b) the total power references dispatch into each unit through optimization. In practice, proportional–integral (PI) controller is widely used in the total power references tracking of AGC in an IDN. In order to further improve the adaptability and control performance of AGC, an online particle swarm optimization (PSO)-based fuzzy tuning approach was proposed for frequency control in an AC microgrid [3] recently, many researchers have been undertaken to design a decentralized control for smart grid. A decentralized control was developed to improve the performance of a single-phase grid-interfacing inverter on component level, which can merely improve the local performance of an inverter. To solve the integration of a single distributed generation unit, of which the storage function is difficult to be constructed and it can only improve the local performance of a generator. In contrast, this paper develops a robust decentralized controller of AGC, which can achieve a coordinated control between multi agents to improve the global performance of the whole system with an easy implementation.[4]

II. WOLF PACK HUNTING

This paper aims to propose a novel MAS stochastic consensus game (MAS-SCG) for the hybrid of homogeneous and heterogeneous MA, in which an MAS collaborative consensus (MAS-CC) will be chosen if a system has many followers, while MAS stochastic game (MAS-SG) [5] will be selected if a system has few leaders. The idea of MAS-SCG originally stems from the group hunting of a wild wolf pack in the harsh environment, which ensures the survival and prosperity of the whole wolf pack via CC, and then wolf pack hunting (WPH) strategy is developed. Under the proposed framework, a continuous information exchange between agents (AGC units) is adopted to rapidly calculate optimal power references, which achieves an optimal coordinated control of each region and electric power autonomy of islanding power grids with increased utilization rate of renewable energy. An islanding smart DN (ISDN) model consisting of multiple distributed generations and micro grids is built to verify the effectiveness of the proposed approach. The decentralized autonomous control of power systems has inspired the active power grid splitting [6] and frequency support of an islanding power grid [7].

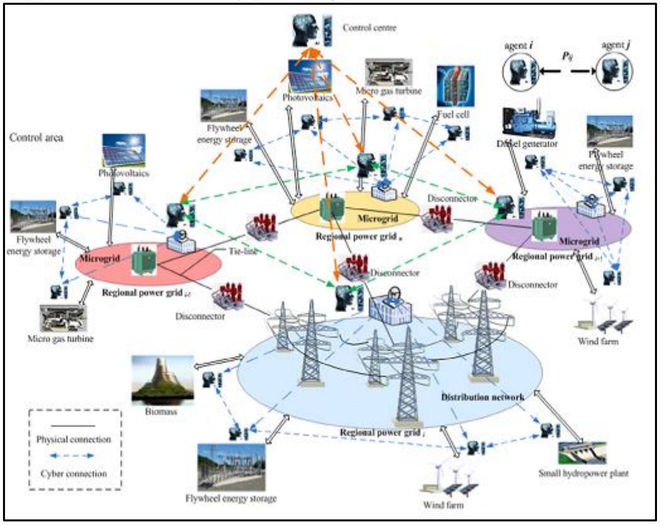

Fig. 1: The framework of decentralized AGC

Currently, decentralized autonomous control has been applied to AGC of micro grids [8], which is very attractive as a virtual power plant (VPP) was introduced for the power system FR. How to effectively integrate multiple micro girds and VPPs into an ISDN to achieve an optimal AGC becomes a very important issue. The framework of decentralized AGC is illustrated by Fig. 1.

WPH is designed by combining MAS-SG and MAS-CC to handle the coordination and distributed region optimization. The conventional AGC for ISDN includes: (a) Obtain the total power references via controller (normally PI controller) based on local frequency deviations; and (b) assign the total power references to each unit via a fixed proportion of the adjustable capacity based on the real-time operation condition. In contrast, WPH based AGC includes: (a) Obtain the total power references via MAS-SG based on local frequency deviations; and (b) the chief firstly tracks the total power references and each unit communicates with its adjacent units, then all units obtain its own power reference through MAS-CC. The application of WPH is not restricted to the centralized calculation and power reference dispatch of a single centralized controller. Actually, if some agents break down unexpectedly, the rest can remain an information exchange and continues to achieve a new consensus. As there often exists more than one communication channels between agents, AGC performance can keep optimal when some communication channels are even faulty. This is due to the information sharing of each agent specified by Fig. 2. Some related concepts are defined as follows:

- Wolf king: This is a control center with MAS-SG among all regions. It communicates with each chief, and sends optimal power references dispatch to them.
- Chief: This is a dispatch end of a whole region. It communicates and coordinates with the wolf king, and sends power references to the patriarch of each family.
- Family: This is a group of units sharing similar regulation features in a region, such as hydro, micro gas turbine, and diesel generator.
- Patriarch: Who is a leader of generation control units (a big wolf in WPH) with significant dispatch capacity, it can achieve a highly active searching and execute complex generation commands independently.
- Family member: Who is a follower of generation control units, however, it can only follow the patriarch behavior and execute simple generation commands.
- Reserve: Who is a standby group of small hydropower units, it will only be put into operation if a load disturbance exceeds 50% of the default value.

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A. MAS-SG framework

A Wolf king adopts multi-agent stochastic game to achieve a control objective for control area and having only one Wolf Pack decentralized win or learn fast policy hill-climbing (λ) method based MAS-SG has been developed by the author Tao Yu[4].

The optimal target state value function $V^{\pi*}(s)$ and strategy $\pi^{*}(s)$ obtained under states in Q-learning can be expressed as follows: [10],[11]

$$V^{\pi*}(s) = maxQ(s,a) \qquad (1)$$

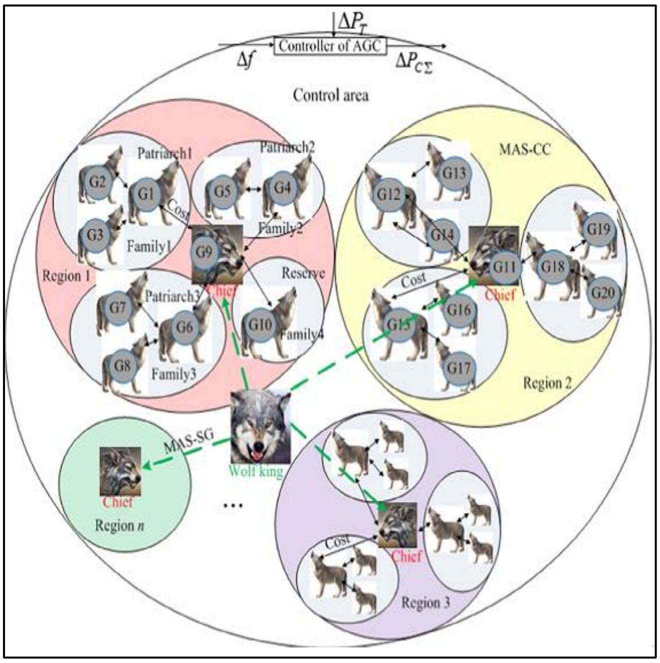

Fig. 2: The multi-area WPH framework

$$\pi^{*}(s) = \arg\max_{a\in A} Q(s,a) \qquad (2)$$

Where A is the set of action. The eligibility trace based on state-action-reward-state-action (λ) is chosen as

$$e_{k+1)}(s,a) = \begin{cases} \gamma\lambda e_{k+1)}+1, & (s,a)=(s_k,a_k) \\ \gamma\lambda e_{k+1)} & otherwise \end{cases} \qquad (3)$$

Where $e_{k+1)}(s,a)$ denotes the denotes the eligibility trace atthe kth iteration used under state s and action a ; γ is the discount factor; and λ is the trace-attenuation factor.

B. MAS- collaborative consensus (MAS-CC) framework

MAS-CC is introduced into WPH, which is adopted by the family members with homogeneous MAS to follow the patriarch of a wolf pack.

1) Graph Theory

The topology of MAS is represented through a directed graph G =(V, E, A) with a set of node V ={v_1, v_2 , … , v_n}, a set of edge E = V × V, and a weighted adjacency matrix B = $[b_{ij}] \in R^{n\times n}$[12]. Here node v_i denotes the ith agent, edge means the relationship among the agents, and constant $b_{ij} \geq 0$ is the weight between v_i and v_j , respectively. A graph G is strongly connected if any vertex can be realized from any other vertex by a directed path. The Laplacian matrix of $L = [l_{ij}] \in R^{n\times n}$ of the graph G can be written as

$$l_{ij} = \sum_{j=1,j\neq 1}^{n} b_{ij}, \quad l_{ij} = -b_{ij}, \quad \forall\neq j \qquad (4)$$

Where L determines the topology of MAS.

2) Design of collaborative consensus

An MAS including of n autonomous agents is regarded as a node in a directed graph G. CC aims to achieve a consensus among each agent, which uses real-time updates of the state after communicating with adjacent agents. Due to the communication delay among agents, the first-order algorithm of a discrete time system is chosen as [13]

$$x_i[k+1] = \sum_{j=1}^{n} d_{ij}[k]\, x_j[k] \qquad (5)$$

Where x_i is the state of the ith agent; k is the discrete time index; and d_{ij} [k] is the (i, j) entry of the stochastic row matrix $D = [d_{ij}] \in R^{n\times n}$ in the kth communication, which is given by

$$d_{ij}[k] = \, |l_{ij}| / \sum_{j=1}^{n} |l_{ij}|, \quad i = 1,2,\ldots\ldots,n. \qquad (6)$$

With the time-invariant communication and constant b_{ij}, a CC can be achieved if and only if the directed graph is strongly connected [14]

III. WOLF PACK HUNTING DESIGNED FOR AGC

This section aims to design WPH for an adaptive coordinated AGC. During each iteration, the wolf king monitors the current operation state online to update the value function and Q-function, and then an action will be executed based on the average mixed strategy

A. *Reward function selection*

In general, absolute value of the frequency deviation | D f | maximizes the long term benefit of control performance and alleviates severe power fluctuations, while generation costs consider the effect of EMS to the economy. As a consequence, a weighted sum of |D f| and C instantaneous is selected as the reward function, in which a larger weighted sum will result in a smaller reward.

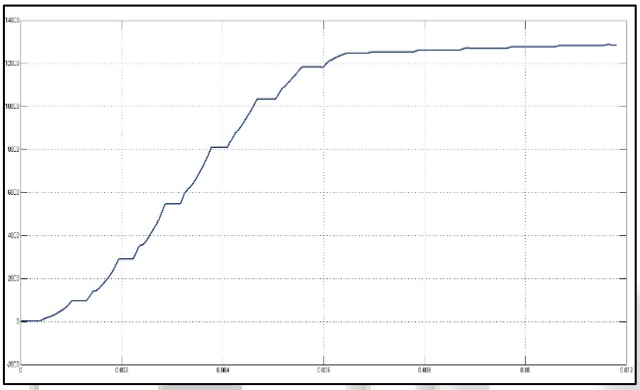

Fig. 3: DC voltage output

The reward function R is written as

$$R(s_{k-1}, s_k, a_{k-1}) = -\mu \mid f \mid \Delta f \mid^{2} C_{instantaneous}/50000 \qquad (7)$$

Where$|\Delta f|$ and $C_{instantaneous}$ indicate the instantaneous absolute values of the frequency deviation and the actual generation costs of all units at the kth iteration. μ and (1- μ) represent the metrics of $|\Delta f|$ & generation costs, respectively. Here μ = 0.5 is chosen [9]

B. *Parameter Setting*

The parameter values used in WPH are given in Table 1.

Sr. No.	Parameter	Symbol	Value
1	Trace-attenuation factor	λ	0.9
2	Discount factor	γ	0.9
3	Q-learning rate	α	0.5
4	Variable learning rate	φ	0.06

Table 1: Parameter Values Used In Wph

C. *Analysis of convergence coefficient ε*

It can be seen from

$$\omega_i[k+1] = \sum_{j=1}^{n} d_{ij}\omega_j[k] + \varepsilon\Delta P_{error} \qquad (8)$$

The convergence coefficient ε determines the convergence rate of algorithm, of which a small value results in a slow convergence while a large value may lead to a non-convergence. Hence, a algorithm Simulation tests have found that convergence rate will be significantly decelerated with a decreased ΔP_{error}, thus a variable convergence coefficient e is proposed to improve the convergence rate. For the leader, $\varepsilon\Delta P_{error}$ is chosen as a constant when the magnitude of ΔP_{error} is less than a specific value, e.g., 10% of the maximum power deviation, such that the convergence rate can be increased. Note that the value of $\varepsilon\Delta P_{error}$ should be properly chosen to guarantee the convergence of algorithm. For a system consisting of n agents, the leader consensus variable is increased by $\varepsilon\Delta P_{error}$ while each agent consensus variable is increased by $\varepsilon\Delta P_{error}/n$ in average. The total AGC power increment is calculated as $\sum(\varepsilon\Delta P_{error}/2n\alpha_i)$ with the termination criterion $\Delta P_{error} \le \Delta P_{error}^{max}$. The sufficient condition for con-vergence is

$$\mid \varepsilon\Delta P_{error} \mid \le \frac{\Delta P_{error}^{max}}{\sum_{i=1}^{n} 1/2n\alpha_i} \qquad (9)$$

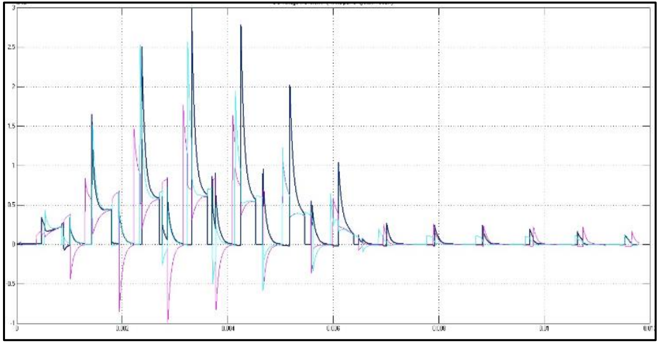

Fig. 4: Frequency Deviation

Where ΔP_{error}^{max} .> 0 is the maximum tolerated power error of Islanded Smart

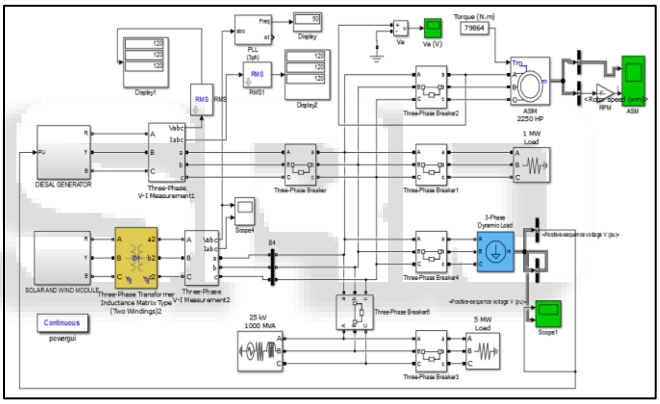

Fig. 5: WPH Simulink model of Microgrid

Distribution Network considering both convergence rate and stability of the algorithm.

IV. SIMULATION AND RESULTS

Simulink model as shown in figure.3 One can find that WPH is convergent, decentralized, strong robust, and has the lowest generation costs. This paper proposes a novel decentralized autonomous control, which has two main advantages as follows:

WPH is based on active power control and area frequency autonomy while the existing automatic voltage control (AVC) is based on reactive power control and node voltage control. This similarity inspires a combination of WPH and AVC for future studies. As a result, the implementation of WPH of a decentralized EMS is feasible with acceptable generation costs. The power generation can be optimized by WPH in the presence of ever-increasing penetration of wind, solar, and flywheel energy storage. Furthermore, the introduction of decentralized autonomy can fully exploit the power generated from the large centralized sources (hydro, thermal, gas, nuclear energy, etc.), small distributed sources (wind, solar, ocean energy, etc.), controllable loads, and static/dynamic storage systems. Note that WPH has the fastest convergence rate for AGC, which is within a control period of 4–16 s. Hence it is adequate for the control design of many small time-scale systems, such as drone group and robot group.

V. CONCLUSION

The contribution of this paper can be summarized as follows:

– An equal incremental principle based WPH is designed by combining MAS-SG and MAS-CC to realize an optimal coordinated control of ISDN, which can simultaneously realize an SGC based on mixed homogeneous and heterogeneous MA.

– A virtual consensus variable has been employed into WPH tore solve topology variation caused by the AGC power exceeding, while the startup and shutdown of units can be trans-formed into an actual and virtual connection between agents. Besides, the use of variable convergence coefficient significantly improves the convergence rate such that an AGC dynamic optimal dispatch can be achieved.

– Simulation results verify that WPH is highly adaptive and robust to the multi-regional, intensively stochastic, and interconnected complex ISDN, which can dramatically increase the utilization rate of renewable energy and reduce generation costs.

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