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Stochastic Scheduling of Renewable and CHP based Microgrids

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***Abstract*—Microgrids (MGs) are considered as a key solution for integrating renewable and distributed energy resources, combined heat and power systems (CHP), as well as distributed energy-storage systems. This paper presents a stochastic programming framework for conducting optimal 24-hour scheduling of CHP-based MGs consisting of wind turbine, fuel cell, boiler, a typical power only unit and energy storage devices. The objective of scheduling is to find the optimal set points of energy resources for profit maximization considering demand response programs and uncertainties. The impact of the wind speed, market and MG load uncertainties on the MG scheduling problem is characterized through a stochastic programming formulation. The paper studies three cases in order to confirm the performance of the proposed model. The effect of CHP-based MG scheduling in the islanded and grid-connected modes as well as the effectiveness of applying the proposed DR program are investigated in the case studies.**

***Index Terms*—Combined heat and power (CHP) system, demand response programs, CHP-based microgrid scheduling, stochastic programming**

I. Introduction

MICROGRID (MG) can be described as a group of controllable loads and distributed energy resources (DER) that can be connected and disconnected from the main grid, and utilized in grid-connected or islanded modes considering certain electrical constraints [1]. The MG concept has recently attracted significant public attention. Integration of DER (comprising renewable sources), combined heat and power systems (CHP), and energy storage technologies in the MGs will result in environmentally friendly, low cost, and reliable energy [2], [3]. Recently, using CHP systems in microgrids has attracted more attention [4]. The primary motivation for incorporating CHP units is providing electrical and thermal energy, simultaneously. During electricity generation process of CHP systems, waste heat is employed to provide thermal energy. This process will result in the improvement of overall system efficiency as well as a significant reduction in the cost of thermal energy generation. It should be mentioned that, in a CHP unit, the power generation boundaries depend upon the heat generation of unit and the heat generation boundaries depend on the power generation of the unit. In [5], [6] the CHP economic dispatch problem is solved considering heat-power dependency characteristics.

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In restructured electricity markets, the MG owner tries to supply the MG electrical and heat demand at minimum cost from various resources such as self-generating facilities and pool market purchase. Therefore, more attention has been attracted on demand response (DR) programs, which aims to energy procurement cost reduction. Demand response program according to the U.S. Department of Energy (DOE) is defined as industrial, residential and commercial customers capability to change energy-consumption patterns in response to changes in the price of electrical energy over time, or to incentive payments in order to accomplish reasonable prices and network reliability.

Increasing penetration of renewable energy sources in electric grid entails inevitable challenges both in operation and management sides due to the uncertain nature of renewable resources like wind in order to maintain the electrical energy production and consumption balance [7], [8]. In addition to the volatility of wind speed, the MG is exposed to market price and its load uncertainty that need to be predicted. Hence, an accurate wind speed, price and load forecast has a decisive influence on the decision making strategies of the MG master in order to proper scheduling of the MG.

The management and scheduling of DERs, including renewable generation in a MG, have been surveyed in many works [9]–[11]. In [11] a dynamic control strategy and modeling for a sustainable MG supplied by wind and solar energy has been presented. The wind energy and solar irradiance changes in combination with load power variations have been envisaged in [11]. Focusing on uncertain nature of renewable sources, the wind speed and solar irradiance forecasting problem in a MG has been studied in [12]. An artificial neural network has been used in [12], to forecast the wind speed. In addition, optimal set points of DERs and storage devices have been determined based on the forecasted data in such a way that the total net emissions and operation cost are minimized, simultaneously. In [13], MG intelligent energy management under cost and emission minimization has been investigated. The paper proposed an approach that can handle uncertainties regarding the fuzzy environment of the overall MG operation and the uncertainty related to the forecasted parameters. Reference [14] proposed a stochastic framework based on scenario generation technique such that the uncertainty associated with the load forecast error, photovoltaic (PV) and wind turbine

(WT) power generation as well as market price would be envisaged in the operation management of MGs. The grid-connected mode is considered in [14] which includes WT, PV, micro-turbine, fuel cell and energy storage devices.

In [15] optimal operation of a MG consisting of fuel cell power plant as well as CHP system is studied using a particle swarm optimization algorithm. Moreover, the effect of different tariff for procuring and selling electricity in each hour of a day has been investigated. A mathematical programming for optimal operation of micro-CHPs in a micro-grid is presented in [16]. In this framework the microgrid is considered in grid-connected mode that can interchange the electricity with the main grid. The objective function of the model is minimizing of total costs while satisfying heat demand of the network.

The conception and role of DR in the MG scheduling is very vital, especially in presence of renewable sources. An overview and a taxonomy for demand side management, analyzes the various types of demand side management are presented in [17]. In [18] fast distributed DR algorithm in smart grid has been provided. In [19], the effect of DR programs on the voltage stability of power systems has been studied in the presence of stochastic wind power generation. A DR energy management scheme for industrial facilities has been proposed in [20] which takes advantage of DER. The proposed DR scheme in [20] is based on the state task network and mixed integer linear programming. In [21], a system-wide demand response management model is presented, which is provided by residential customers in order to coordinate demand response. An incentive-based program (IBP) considering the real-time pricing and bi-directional operation is presented in [22]. Real-time pricing (RTP) scheme has been proposed for residential load management in [23] and for large electric utilities in [24]. In [23], an automatic scheme for optimal operation of each appliance in households has been presented in presence of RTP tariff. A game theoretic consumption scheduling framework has been proposed in [25], which incorporates renewable energy generation. The proposed optimization scheme in [25] is based on the mixed integer programming to schedule consumption scheme for residential consumers. In [26] an agent-based demand side management framework is presented in which customers encouragement is performed through a priority-based incentive mechanism. A multi-objective MG self-scheduling problem is investigated in [27], considering DR program. The paper modeled DR program as a virtual generation unit. The objective function comprises of minimizing the total operational cost of the CHP system and the emission minimization of distributed generation units in a MG. Moreover, in the proposed DR program the load is considered to be curtailable in the time intervals.

The current paper focuses on the optimal scheduling of CHP-based MGs. The work presents a new scheme in order to model the DR program in the MG, which has shown successful executions in CHP-based MG scheduling. The objective of the scheduling problem is to satisfy both electrical and heat demand of the MG as well as take advantage of the opportunity, to sell any excess electricity to the main grid in high price hours or to procure the energy from the grid at low market price time intervals. In addition, a DR program has been presented to have more successful participation in the power market. In the implemented DR program the MG load will be shifted from high market price time intervals to low market price time intervals to take the most advantage of grid-connected mode and market participation. The amount of responsive load could be different in different time intervals. The MG is assumed to possess a power-only unit, three WT units, fuel cell unit, a boiler unit, two CHP units, a heat buffer tank and electrical energy storage device. Moreover, the MG scheduling problem considers the units startup and shutdown costs as well as operating costs. In addition, the solution of the scheduling problem complies with the technical constraints of the units, consisting of minimum and maximum capacity of units and dual dependencies of heat and power production in the CHP units. The uncertainties pertaining to wind turbine generation, MG demand and market price in the scheduling problems is characterized via scenarios. In addition, the periodic or seasonal pattern of load and price processes has been considered in the scenario generation procedure using seasonal ARIMA (SARIMA) models. A new scheme is used to generate wind speed scenarios. In addition, fast backward reduction method is used as scenario reduction technique in order to handle the large scale problem. Three case studies are scrutinized in the paper. The first case studies the scheduling problem when MG is in the islanded mode. The second case evaluates the effect of grid-connected mode in the CHP-based MG scheduling problem. Finally, third case studies the scheduling problem by not considering the DR program in order to highlight the effectiveness of applying the DR program in maximizing total profit. The results of all scheduling strategies are discussed and compared in order to highlight the economic advantages of implementing the proposed strategy. The contributions of the paper can be summarized as follows:

- Short-term scheduling problem of CHP-based MGs is conducted. In the proposed framework, the grid-connected and islanded modes of MG have been studied. Total heat and power demand of MG has been satisfied with minimum cost. In the proposed model, the most technical constraints of units are taken into account especially dual dependencies of heat and power production in the CHP units.
- Wind turbine generation, power demand and pool prices are considered as stochastic processes in the scheduling problem. The power demand and pool prices variables are forecasted using

SARIMA models.
- Non-convex feasible operation region in different types of CHP units is formulated as a mixed integer linear formulation in the scheduling problem of CHP-based MGs.
- The DR program is implemented in the stochastic programming problem in order to have more successful participation of CHP-based MGs in the power market. In the implemented DR program, the amount of responsive load can vary in different time intervals.

The rest of this paper is organized as follows: In *Section* III, detailed discussions on the proposed method and problem formulations are presented. *Section* IV presents simulation studies and discussions on the results. Finally, the conclusion is provided in *Section* V.

II. Preliminaries

A. Stochastic programming

The stochastic programming approach constitutes a suitable tool to make decisions under uncertainty and reveals the fact that new information about the uncertain data becomes known as time evolves along the planning horizon. In a multi-stage stochastic programming the decisions made for a stage are not affected with the information arriving in following stages [28]. The probability description about the uncertain data could be visualized through a scenario tree. A scenario tree comprises a set of nodes and branches. Node represents the state of the problem. Branch shows transition between stages where scenarios are realized. The first node of the problem is called Root and the nodes of the last stage are called Leaves. Each way between the root node and a leaf is a scenario. The number of nodes in the last stage equals the number of scenarios.

B. ARMA models

ARMA processes are stochastic processes which are used to analyze time series. An ARMA*(p, q)* process can be expressed as [29]:

$$y_t = \sum_{j=1}^{p} \phi_j y_{t-j} + \varepsilon_t - \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \qquad (1)$$

In which p is the number of autoregressive parameters $\phi_1, \phi_2, ..., \phi_p$, and q stands for the number of moving average parameters $\theta_1, \theta_2, ..., \theta_q$. The term ε_t is the error term and stands for a normal stochastic process with mean zero and variance equal to ${\sigma_\varepsilon}^2$.

In this paper the stochastic processes describing wind speed behavior are modeled using ARMA models. Two major assumptions concerning the use of ARMA models are to assume that the stochastic process is stationary and the associated marginal distribution is Gaussian. It should be mentioned that there are some methods to generate ARMA models for other distributions than the Guassian [29]. In order to accomplish stationary for the mean, the differencing procedure would be applied to ARMA model, which leads to ARIMA models. The ARIMA models are defined by three parameters *(p, d, q)*, which stand for the number of autoregressive terms, the differentiating order, and the number of moving-average terms, respectively. The general statement of an ARIMA model with parameters *(p, d, q)* can be as follows.

$$(1 - \sum_{j=1}^{p} \phi_j B^j)(1 - B)^d y_t = (1 - \sum_{j=1}^{q} \theta_j B^j)\varepsilon_t \qquad (2)$$

where, B is the backshift operator. In order to forecast the price and load processes in the MG scheduling problem, seasonal autoregressive integrated moving average models (SARIMA) are required. Therefore, the SARIMA model, considering seasonality of order S, with parameters $(p, d, q) * (P, D, Q)_S$ is indicated as:

$$(1 - \sum_{j=1}^{p} \phi_j B^j)(1 - \sum_{j=1}^{P} \Phi_j B^{jS})(1 - B)^d (1 - B^S)^D y_t$$
$$= (1 - \sum_{j=1}^{q} \theta_j B^j)(1 - \sum_{j=1}^{Q} \Theta_j B^{jS})\varepsilon_t \qquad (3)$$

Equation (3) is stated with a seasonal component of P autoregressive parameters $\Phi_1, \Phi_2, ..., \Phi_P$, Q moving average parameters $\Theta_1, \Theta_2, ..., \Theta_Q$, and a differentiation order D.

III. Problem formulation

A. CHP-based microgrid scheduling model

The objective of the optimal scheduling of the CHP-based MG is maximizing the profit obtained from hourly electrical market revenues over 24-hour time horizon in the presence of DR programs and uncertainties. The main source of uncertainties in MG scheduling problem are the wind speed, day-ahead market price and the MG power load. In this paper, in order to model the consequence of these uncertainties, multistage stochastic programming procedure has been employed.

The scenario set in the problem consists of the electricity price, the wind speed and the MG load at each hour of the decision making horizon and their associated probabilities. Since the power generation of units, should be determined before realization of uncertain stochastic processes, they are the first stage or here-and-now decisions and they do not depend on the scenario realization. Other state variables such as state of charge and the power for selling or buying from the market are second stage decisions or wait-and-see variables.

B. Uncertain variables in CHP-based microgrid scheduling

The load forecast is a major source of uncertainty in MG short term scheduling. The variable load cannot be easily forecasted as it depends upon variations in hourly prices, weather conditions, and consumers decisions.

Variable renewable generation is another source of uncertainty. The uncertain nature of the renewable resources will cause the produced power volatility. The variable wind speed typically does not follow a reduplicative pattern in the daily operation of MGs and depends upon site and weather conditions [30]. Hence, the precise forecasting of wind turbine generation requires sophisticated methods. Radiation forecast is not as volatile as wind speed. Therefore, the current paper does not deal with this instance as an uncertain variable, in order to simplify the solving procedure.

The last uncertainty related to MG scheduling is the pool market price. Pool market price will depend upon several uncertain factors, including offers by market participants and participation of consumers with responsive load. The market price volatility may cause the commitment and dispatch of units in the MG scheduling problem.

In this paper, a CHP-based MG scheduling model considering load, renewable generation, and market prices uncertainty is proposed.

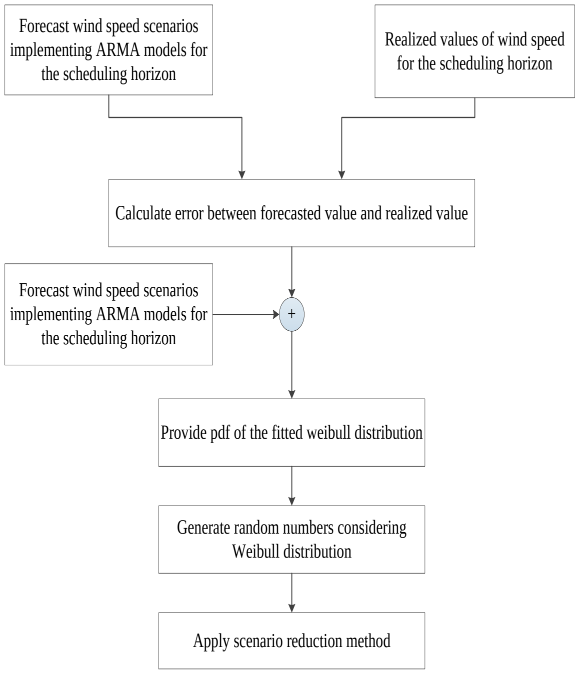

Fig. 1. Flowchart for wind speed scenario generation process

C. Scenario generation and reduction

a) Pool price and power demand scenarios: The stochastic processes of pool price and the MGs power demand are modeled implementing SARIMA models.

Future pool prices and demand scenarios for one day could be generated considering the daily and weekly seasonality of both series, by using the SARIMA methods described in the equations (4) and (5), respectively [29], [31]:

$$(1-\phi_1^{pr}B-\phi_2^{pr}B^2)(1-\phi_{24}^{pr}B^{24})(1-\phi_{168}^{pr}B^{168})\log(\lambda_t)= (1-\theta_1^{pr}B-\theta_2^{pr}B^2)(1-\theta_{168}^{pr}B^{168})\varepsilon_t^{pr} \tag{4}$$

$$(1-\phi_1^{L}B)(1-\phi_{24}^{L}B^{24})(1-\phi_{168}^{L}B^{168})\log(load_t^0)= (1-\theta_{168}^{L}B^{168})\varepsilon_t^{L} \tag{5}$$

where, ϕ_1^{pr}, ϕ_2^{pr}, ϕ_{24}^{pr}, ϕ_{168}^{pr} and ϕ_1^{l}, ϕ_{24}^{l}, ϕ_{168}^{l} are autoregressive parameters related to market price and load, respectively. $\theta_1^{pr}, \theta_2^{pr}, \theta_{168}^{pr}$ and θ_{168}^{l} are the moving average parameters of market price and load, respectively. Moreover, λ_t and $load_t^0$ are the market price and MG electric load at time t, respectively, It should be mentioned that, in the ARIMA models logarithm function is used in order to stabilize the variance of series. Moreover, the hourly historical data of load and price are used to model the behavior of load and price, respectively. The parameters of SARIMA models (4) and (5) are obtained using appropriate MATLAB function. In order to model the load and price behavior the adjusted parameters of SARIMA are computed using MATLAB appropriate function. Afterwards, these adjusted parameters are used to forecast the load and price parameters of the MG.

Since computational requirements for solving the stochastic programming problems depend upon the number of scenarios, an effective scenario reduction method is essential for solving large scale problems. The reduction procedure would be a scenario-based approximation with a smaller number of scenarios and close to the original system. In this paper, fast backward reduction method is used as scenario reduction technique [32]. In the current paper, the SCENRED tool under GAMS environment has been implemented for scenario reduction process of day-ahead market prices and MG power demand.

b) Wind speed scenarios: the wind speed does not follow a certain trend as pool price or load processes. Hence, forecasting the wind speed scenarios needs a powerful technique to schedule the MG more practically. The flowchart of scenario generation procedure for wind speed, which is adopted from [33], has been presented in Fig.1. To consider the impact of the wind power production uncertainty on the MG scheduling problem, the wind speed for each time period of scheduling horizon is forecasted implementing the ARMA models. Afterwards, the error of the scenarios would be compared and updated according to some realized values of wind speed for the scheduling horizon. This error is added to the forecasted value. In the next step, the forecasted wind speed frequency distribution is generated for each time interval of scheduling horizon, which follows a Weibull distribution. Next, wind power scenarios for the each hour of day are generated by using shape and scale parameters of Weibull distribution. Finally, the reduced scenarios with corresponding probabilities are generated using SCENRED tool under GAMS environment.

D. Demand response model

The main aim of the DR program is to shift the load of MG from high market price time intervals to the low market price time intervals. In the DR program,

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the MG can shift only the limited portion of the load which can vary during the scheduling horizon. The final load after implementing the DR program could be stated as:

$$load_t^\omega = (1 - DR_t^\omega) \times load_t^{0,\omega} + SL_t^\omega \quad (6)$$

where, $load_t^{0,\omega}$ and $load_t^\omega$ indicates the load before and and after applying DR program. DR_t^ω states for the percentage of load shifting from hour t, and SL_t^ω indicates the shifted load from other hours to hour t in scenario ω. The portion of the load which can be shifted to other time intervals can be represented as following:

$$DR_t^\omega \leq DR^{\max} \quad (7)$$

where, $DR^{\max}$ states for the maximum load the MG which can be shifted. The following constraint limits the increased load in each interval and inhibits the excessive shift of load in the intervals. In other words, this constraint applies the technical constraints related to the maximum amount of increased load.

$$0 \leq load_t^{\omega,IL} \leq IL_t^\omega \times load_t^{0,\omega} \quad (8)$$

where, IL_t^ω is the amount of increased load at time t. $load_{\omega,t}^{IL}$ could be defined as:

$$load_t^{\omega,IL} = SL_t^\omega - (DR_t^\omega \times load^{0,\omega}_{t}) \quad (9)$$

The following constraint limits the incremental load, IL_t^ω :

$$IL_t^\omega \leq IL^{\max} \quad (10)$$

In this paper it is considered that the total daily consumed energy of the MG should be the same before and after implementing the DR programs. This constraint can be stated as following:

$$\sum_{t=1}^{24} SL_t^\omega = \sum_{t=1}^{24} DR_t^\omega \times load^{0,\,\omega}_{t} \qquad \forall \omega \in \Omega \quad (11)$$

Hence, the MG would be able to supply all its electrical demand with less cost.

E. Objective function

In the CHP-based MG scheduling problem the objective function (OF) is maximizing the total profit, while supplying the total power and heat demand of the MG. The revenue of the MG comes from selling the excess electricity to the market when it is operated in the grid connected mode. The cost of the MG includes the units operational cost and units startup and shutdown costs as well as cost of buying energy from the pool in the grid connected mode. It should be mentioned that in order to reduce the frequently turning on and off problems of units, a term illustrating the start-up and shut-down costs is included in the objective function [16]. It is assumed that the consumer contains two varieties of CHP units, WT, fuel cell, typical power only unit, boiler unit, heat buffer tank, electrical energy storage device and responsive load. Hence, the corresponding OF can be mathematically stated as:

$$\begin{aligned} OF = \sum_{t=1}^{24} \{ & \sum_{\omega\in\Omega} \pi^\omega \{ (P_t^{\omega,sale} \times \lambda_t^\omega) - (P_t^{\omega,buy} \times \lambda_t^\omega) \} \\ & - \sum_{i=1}^{N_{CHP}} C_i(P^{CHP}, H^{CHP}) - \sum_{j=1}^{N_p} C_j(P^P) \\ & - \sum_{k=1}^{N_b} C_k(H^B) - \sum_{l=1}^{N_F} C_l(P^F) \\ & - \sum_{h\in i,j,k,l} (CSU_{h,t} \times SU_{h,t} + CSD_{h\,,t} \times SD_{h\,,t}) \} \end{aligned} \quad (12)$$

$$\pi^\omega = \pi^{pr} \times \pi^l \times \pi^{WT} \quad (13)$$

where, π^ω indicates the probability of scenario ω. $P_t^{\omega,sale}$ and $P_t^{\omega,buy}$ are the amount of power sold and bought to/from the market, respectively. Superscripts CHP, P, B and F refers to the CHP unit, conventional power only, boiler and fuel cell units, respetively. Indices i, j, k and l are indexes for cogeneration units, conventional units, boilers and fuel cell units, respectively. According to equation (13) the probability of ωth scenario is obtained by multiplying the probabilities of market price, load and wind turbine generation.The function, C_t,represents the total operation cost of units. The total operation cost of a CHP unit could be defined as [34]:

$$\begin{aligned} C(P^{CHP}, H^{CHP}) &= a \times P^2 + b \times P + c \\ &+ d \times H^2 + e \times H + f \times H \times P \end{aligned} \quad (14)$$

Referring to the Eq. (14), all variables are related to the CHP units. In addition, a, b, c, d, e and f are cost function coefficients of CHP units, which is function of both heat and power production of units. The operation cost of a conventional power and heat only units and fuel cell units are considered to be linear and respectively can be formulated as following:

$$C_j(P^P) = \psi \times P^P \quad (15)$$

$$C_k(H^B) = \gamma \times H^B \quad (16)$$

$$C_l(P^F) = \chi \times P^F \quad (17)$$

where,ψ, γ and χ are cost function coefficients of power and heat only units and fuel cell units, respectively.It should be mentioned that the operation cost of the wind units are low and could be neglected [35]. The binary variables $SU_{h,\,t}$ and $SD_{h,\,t}$ are defined to model the start-up and shut-down status of the units, as following:

$$SU_{h,\,t} = V_{h,\,t} \times (1 - V_{h\,,t-1}) \qquad h \in i, j, k, l \quad (18)$$

$$SD_{h,t} = (1 - V_{h,t}) \times V_{h,t-1} \qquad h \in i, j,\, k, l \quad (19)$$

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F. Generation units constrains

1) CHP units: It should be mentioned that the power and heat generations of the CHP units are dually dependent and could not be controlled separately. There are two types of feasible operating region (FOR) for CHP units [36]. The first type and second type FOR of a CHP unit are portrayed in Fig. 7. The first type FOR can be characterized using linear representation and Eqs. (20)-(24) model the FOR in the MG scheduling problem [37].

$$P_{i,t}^{CHP} - P_{i,A}^{CHP} - \frac{P_{i,A}^{CHP} - P_{i,B}^{CHP}}{H_{i,A}^{CHP} - H_{i,B}^{CHP}}(H_{it}^{CHP} - H_{i,A}^{CHP}) \leq 0 \tag{20}$$

$$P_{it}^{CHP} - P_{i,B}^{CHP} - \frac{P_{i,B}^{CHP} - P_{i,C}^{CHP}}{H_{i,B}^{CHP} - H_{i,C}^{CHP}}(H_{it}^{CHP} - H_{i,B}^{CHP}) \geq -(1 - V_{it}) \times M \tag{21}$$

$$P_{it}^{CHP} - P_{i,C}^{CHP} - \frac{P_{i,C}^{CHP} - P_{i,D}^{CHP}}{H_{i,C}^{CHP} - H_{i,D}^{CHP}}(H_{it}^{CHP} - H_{i,C}^{CHP}) \geq -(1 - V_{it}) \times M \tag{22}$$

$$0 \leq H_{it}^{CHP} \leq H_{iB}^{CHP} \times V_{it} \tag{23}$$

$$0 \leq P_{it}^{CHP} \leq P_{iA}^{CHP} \times V_{it} \tag{24}$$

where, M represents a sufficient large number, and indices A, B, C and D are four marginal points of the FOR in the first type of CHP unit. Equation 20 formulates the area under the curve AB. Equation (21) models the area upper the curve BC, and the upper area of curve CD is represented implementing Eq. (22). According to the Eqs. (21) - (22), for a decommitted unit ($V_{i,t} = 0$) the output power would be zero. Also, the heat and power generation for a decommitted unit must be set to zero which is imposed by Eqs. (23) and (24), respectively. As can be seen from Fig. 3, the FOR of type two is non-convex which can be divided into two convex sub-regions I and II, according to Fig. 3. The type 2 FOR is enclosed by the boundary curve ABCDEFG. In this case by implementing the traditional formulation, like as the first FOR type formulation, the gray region (FEG) would not be envisaged. Hence, this non-convex region is handled by implementing binary variables X_1 and X_2 [36]. Therefore, the non-convex FOR would be divided into two convex sub-regions I and II. the following equations have been considered to model the FOR of CHP unit in the MG scheduling problem, [37]:

$$P_{i,t}^{CHP} - P_{i,B}^{CHP} - \frac{P_{i,B}^{CHP} - P_{i,C}^{CHP}}{H_{i,B}^{CHP} - H_{i,C}^{CHP}}(H_{it}^{CHP} - H_{i,B}^{CHP}) \leq 0 \tag{25}$$

$$P_{i,t}^{CHP} - P_{i,C}^{CHP} - \frac{P_{i,C}^{CHP} - P_{i,D}^{CHP}}{H_{i,C}^{CHP} - H_{i,D}^{CHP}}(H_{it}^{CHP} - H_{i,C}^{CHP}) \geq 0 \tag{26}$$

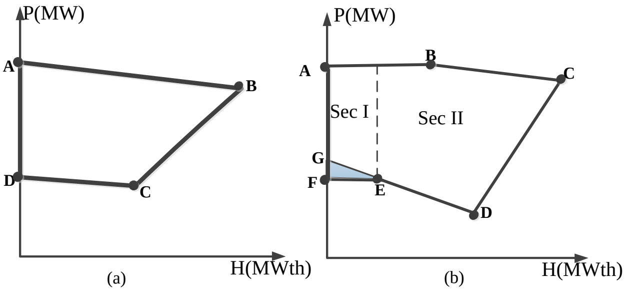

Fig. 2. Power-heat feasible region for a CHP units a) type 1 b) type 2.

$$P_{i,t}^{CHP} - P_{i,E}^{CHP} - \frac{P_{i,E}^{CHP} - P_{i,F}^{CHP}}{H_{i,E}^{CHP} - H_{i,F}^{CHP}}(H_{it}^{CHP} - H_{i,E}^{CHP}) \geq -(1 - X_1) \times M \tag{27}$$

$$P_{i,t}^{CHP} - P_{i,D}^{CHP} - \frac{P_{i,D}^{CHP} - P_{i,E}^{CHP}}{H_{i,D}^{CHP} - H_{i,E}^{CHP}}(H_{it}^{CHP} - H_{i,D}^{CHP}) \geq -(1 - X_2) \times M \tag{28}$$

$$H_{i,t}^{CHP} - H_{i,E}^{CHP} \geq -(1 - X_{2t}) \times M \tag{29}$$

$$H_{i,t}^{CHP} - H_{i,E}^{CHP} \leq (1 - X_{1t}) \times M \tag{30}$$

$$X_{1t} + X_{2t} = V_{i,t} \tag{31}$$

$$0 \leq H_{it}^{CHP} \leq H_{i,C}^{CHP} \times V_{it} \tag{32}$$

$$0 \leq P_{it}^{CHP} \leq P_{i,A}^{CHP} \times V_{it} \tag{33}$$

In the second type, again indices A, B, C, D, E and F states the corner points of the FOR pertaining to Fig. 2-b. Equation (25) introduces the area under the curve BC. The area upper the curve CD is described using (26). The upper area of curves EF and DE are defined using (27) and (28), respectively. In the Eqs. (27) - (30), $X_{1t} = 1$ ($X_{2t} = 1$) means that the CHP unit operates in the first (second) convex section of FOR. According to Eq. (31), the operation region of CHP unit would be either I or II when the unit is ON and none of them when the unit is OFF. In addition, for a decommited unit, Eqs. (32) and (33) will set the heat and power generation to zero.

2) Power only, heat only and fuel cell units constraints: The capacity limits of power and heat only units and fuel cell unit can be expressed as below:

$$P_j^{P,\min} \times V_{j,t} \leq P_{j,t}^P \leq P_j^{P,\max} \times V_{j,t} \tag{34}$$

$$H_k^{b,\min} \times V_{k,t} \leq H_{k,t}^b \leq H_k^{b,\max} \times V_{k,t} \tag{35}$$

$$P_l^{F,\min} \times V_{l,t} \leq P_{l,t}^F \leq P_l^{F,\max} \times V_{l,t} \tag{36}$$

3) Wind power constraint: The total available wind power of a WT is a function of the wind speed and turbine characteristics and can be modeled by Eq. (37) as follows [35].

$$P_{m,t}^{'\omega,WT} = \begin{cases} 0 & V_t < V^{CI}, V_t > V_m^{CO} \\ P_{\max}^{WT} \times \left(\frac{V_t - V^{CI}}{V^R - V^{CI}}\right) & V^{CI} \leq V_t \leq V^R \\ P_{\max}^{WT} & V^R \leq V_t \leq V^{CO} \end{cases} \tag{37}$$

in which, V_m^{CI}, V_m^{CO}, V_m^{R} and $V_t^{\omega,WT}$ are, cut-in, cut-out, rated and instantaneous wind speed. Also, $P_{m,t}^{'\omega,WT}$ and $P_{\max}^{WT}$ are available and maximum wind power, respectively. The generated power of the wind turbine m at time period t is restricted to the available wind power. Also wind power spillage is allowed. The algorithm decides about utilizing renewable generation considering the total cost, the operational constraints and the MG power and heat demands. The following constraint enforces this restriction:

$$P_{m,t}^{\omega,WT} \leq P_{m,t}^{'\omega,WT} \tag{38}$$

4) Electrical energy storage device: Energy balance constraint of the storage can be explained as:

$$E_t^{\omega} = E_{t-1}^{\omega} + \eta_{cha} P_t^{\omega,cha} \Delta t - \frac{1}{\eta_{disch}} P_t^{\omega,disch} \Delta t \tag{39}$$

In which, η_{cha} and η_{disch} are charge and discharge efficiency of the battery, respectively. The limits of charging power, $P_t^{\omega,cha}$, discharging power, $P_t^{\omega,disch}$, and storage capacity, E_t^{ω}, are enforced using the following constraints.

$$\underline{E} \leq E_t^{\omega} \leq \bar{E} \tag{40}$$

$$\underline{P}^{cha}.{\alpha_t}^{\omega,cha} \leq P_t^{\omega,cha} \leq \bar{P}^{cha}.{\alpha_t}^{\omega,cha} \tag{41}$$

$$\underline{P}^{disch}.{\beta_t}^{\omega,dsch} \leq P_t^{\omega,disch} \leq \bar{P}^{disch}.{\beta_t}^{\omega,dsch} \tag{42}$$

$${\alpha_t}^{\omega,cha} + {\beta_t}^{\omega,dsch} = 1 \tag{43}$$

It should be noted that the battery does not charge and discharge simultaneously because of the additional and unnecessary cost of charge and discharge efficiency deterioration. Therefore, binary variables ${\alpha_t}^{\omega,cha}$ and ${\beta_t}^{\omega,dsch}$ are implemented to model the status of energy storage. In the Eqs. (41)-(43), ${\alpha_t}^{\omega,cha} = 1$ (${\beta_t}^{\omega,dsch} = 1$) means that the energy storage is charging (discharging) at time interval t related to the scenario ω. These limitations will force the storage device to buy and charge energy at low market price hours and sell it at high market price hours.

5) Heat buffer tank: The heat buffer tank has been developed from the model introduced in [16]. The heat buffer tank is disposed to the CHP units and the boiler units. In the proposed facility, the heat storage is also possible. The total produced heat $\bar{H}_t$ could be stated as:

$$\bar{H}_t = \sum_{i=1}^{N_{CHP}} H_{i,t}^{CHP} + \sum_{k=1}^{N_b} H_{k,t}^{b} \tag{44}$$

As the heat disposed to the heat buffer tank is effected by the loss (β_{loss}) and extra heat generation (β_{gain}) during shut-down and start-up periods, respectively, the real heat, H_t, which the buffer would be supplied, is as following [16]:

$$H_t = \bar{H}_t - \beta_{loss} SU_{h,t} + \beta_{gain} SD_{h,t} \qquad h \in i,k \tag{45}$$

Hence, the available heat in the heat buffer tank, B_t, could be calculated as:

$$B_t = (1-\eta) B_{t-1} + H_t - H_t^D \tag{46}$$

where, η is the heat loss rate for the heat buffer tank. Moreover, the capacity of heat storage is restricted as:

$$B_{\min} \leq B_t \leq B_{\max} \tag{47}$$

In the paper, the practical state of heat storage system is simulated by considering the ramping up/down rates as follow:

$$B_t - B_{t-1} \leq B_{\max}^{ch\arg e} \tag{48}$$

$$B_{t-1} - B_t \leq B_{\max}^{disch\arg e} \tag{49}$$

G. Power balance

The following constraint expresses that the supplied power by all of the units and the one supplied by network would satisfy the total demand considering DR programs, in each scenario and every hours of the scheduling horizon.

$$\begin{aligned} &P_t^{\omega,buy} + \sum_{i=1}^{N_{CHP}} P_{i,t}^{CHP} + \sum_{j=1}^{N_P} P_{j,t}^{P} + \sum_{l=1}^{N_F} P_{l,t}^{F} + \sum_{m=1}^{N_{WT}} P_{m,t}^{\omega,WT} \\ &+P_t^{\omega,disch} = P_t^{\omega,Sale} + \{(1-DR_t^{\omega}) \times load_t^{0,\omega} \\ &+SL_t^{\omega}\} + P_t^{\omega,cha} \qquad \forall t,\omega \end{aligned} \tag{50}$$

IV. SIMULATION STUDIES

In this section, at first the structure of the considered microgrid is illustrated and after that the simulation results of optimal operation scheduling is presented.

A. Microgrid structure

In the paper, three case studies have been scrutinized:

Case 1: CHP-based MG scheduling in islanded mode considering volatility of market price, MG load and wind speed

Case 2: CHP-based microgrid scheduling in grid connected mode

Case 3: Impact of DR program on the MG scheduling

In the case studies 2 and 3 the MG is able to exchange (sell or procure) the power with the network according to the pool market prices. The proposed stochastic programming model is applied to a typical microgrid depicted in Fig. 3. According to Fig. 3 the considered MG in the case studies, comprises WT units, two cogeneration units with deferent FORs, one boiler unit, a power only unit, an energy storage device and a heat buffer tank unit along with the fixed and responsive electrical demand and a fixed thermal demand. Both $DR_{\max}$ and $inc_{\max}$ are assumed to be 30%. Characteristics of the energy storage device and heat buffer tank are presented in Tables I and II, respectively. The startup and shutdown cost of units

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TABLE I
CHARACTERISTICS OF ENERGY STORAGE DEVICE.

Characteristics	Value	Characteristics	Value
$\bar{P}^{cha}$ (MW)	3	$\underline{E}$ (MW h)	0
$\underline{P}^{cha}$ (MW)	0	$\bar{E}$ (MW h)	6
$\bar{P}^{disch}$ (MW)	3	η_{cha}	0.9
$\underline{P}^{disch}(MW)$	0	η_{disch}	0.9

TABLE II
CHARACTERISTICS OF THE HEAT BUFFER TANK.

β_{gain}	β_{loss}	η	$B_{\max}^{charge}$	$B_{\max}^{discharge}$	$B_{\max}$	$B_{\min}$
0.3	0.6	1%	2	2	7	0

TABLE III
ECONOMIC DATA OF GENERATION UNITS.

Unit/ characteristic	CSU	CSD
CHP unit 1	20	20
CHP unit 2	20	20
Power-Only	12	12
Heat-Only unit	9	9
Fuel cell	0.0207	0.0207

TABLE IV
CHARACTERISTICS OF THE HEAT BUFFER TANK.

Unit	a	b	c	d	e	f
CHP unit 1	0.0435	36	12.5	0.027	0.6	0.011
CHP unit 2	0.0345	14.5	26.5	0.03	4.2	0.031

are provided in Table III. The minimum and maximum power generation of fuel cell are considered to be 3 and 30kW, respectively [14]. Table IV provides the cost function coefficients of cogeneration units. The cost functions of heat-only, power-only and fuel cell units are supposed to be linear and expressed in Eqs. (51) - (53), respectively. The forecasted heat demand of MG is illustrated in Fig. 4. The FOR of cogeneration units is depicted in Fig. 5. The WTs parameters are $V_{CI} = 3.5\,(m/s)$, $V_{CO} = 25\,(m/s)$ and $V_R = 11.9\,(m/s)$ [38] with maximum power output of 0.7, 0.8 and 0.9 MW. The uncertain nature of MG scheduling problem is modeled through a multi-stage stochastic process. The uncertainty related to wind speed is modeled through the proposed method. Moreover, the stochastic processes of market price and MG load are modeled through the SARIMA models. The hourly historical data of load, price [39] and wind speed [40] are used to model the stochastic behavior of these parameters. In addition, 200 scenarios have been generated for each uncertain parameter. Implementing the scenario reduction method, 5 scenarios have been used in the studied cases for each parameter, which will result in total 125 scenarios, considering three uncertain parameters in the problem. Finally, mathematical modeling of the CHP-based MG scheduling problem under stochastic process is solved by using SBB/CONOPT solver [41] under General Algebraic Modeling System (GAMS) environment [42].

$$C_{k,t}^{B} = 23.4 \times H_{k,t}^{b} \qquad 0 \le H_{k,t}^{b} \le 5\,MWth \qquad (51)$$

$$C_{j,t}^{P} = 50 \times P_{j,t}^{p} \qquad 0 \le P_{j,t}^{p} \le 1.5\,MW \qquad (52)$$

$$C_{1,t}^{F} = 40 \times P_{1,t}^{F} \qquad 0.003 \le P_{1,t}^{F} \le 0.03\,MW \qquad (53)$$

B. Simulation results

1) Case study 1: CHP-based MG scheduling in islanded-mode: In this case the MG scheduling problem is solved using proposed stochastic formulation. The scenario generation methods have been employed

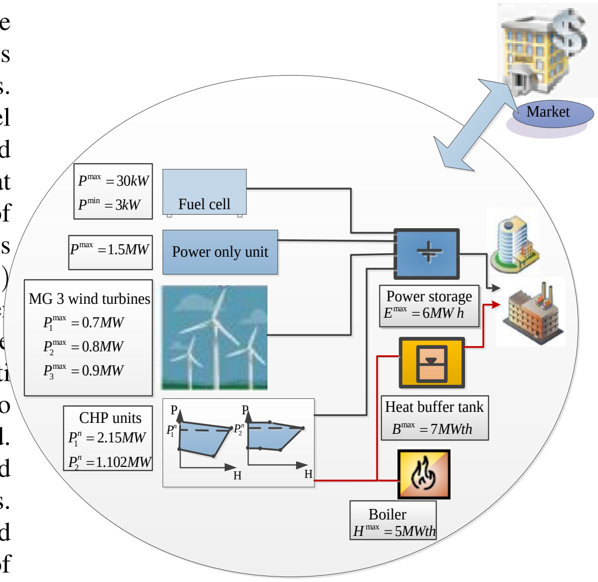

Fig. 3. Typical microgrid test system.

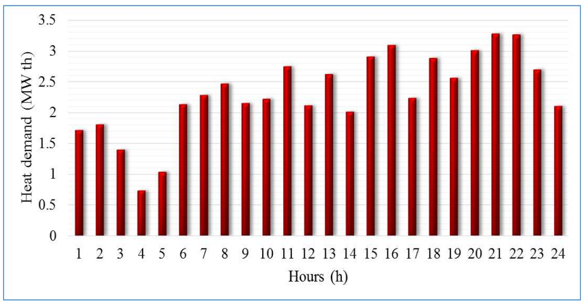

Fig. 4. Forecasted heat demand.

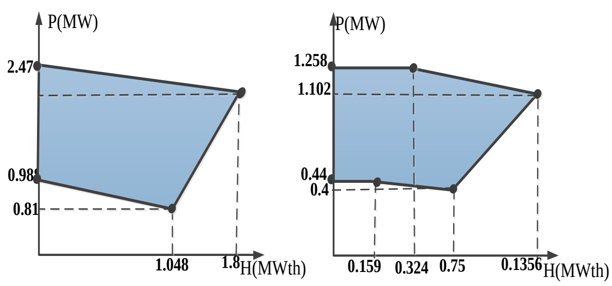

Fig. 5. Power-heat feasible region for CHP units a) unit 1 b) unit 2.

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TABLE V
SIMULATION RESULTS OF CASE STUDIES.

	Generation cost	Revenue from the sale of power	Cost of buying power	Value of objective funct
Case 1	$2,255.709	—-	—-	-$2,255.709
Case 2	$3,754.529	$6,248.144	$68.961	$2,424.654
Case 3	$3,641.380	$5,939.722	$112.243	$2,186.1

to generate the proper scenarios of hourly load, market price and wind energy generation. The MG is considered in islanded mode. Moreover, all technical and economic constraints have been envisaged. Table V summarizes the results of case 2. According to Table V, the cost of MG energy supply would be $2,255.709. The CHP units and WTs will supply about 96% and 4% of total demand, respectively. In this case, wind power generators will not produce power in their maximum capacity at all hours, in spite of their zero operation cost. This fact is due to the MG heat demand. The CHP units will produce heat to supply the demand. Hence, the CHP units FOR will cause the units to produce power as well as thermal energy.

2) Case study 2: CHP-based MG scheduling in grid-connected mode: In the second case the effect of exchanging the electrical energy with the grid in the grid connected MG is studied. The MG scheduling problem is solved considering all technical and economic constraints as well as DR program. The results regarding case 2 are presented in Table V. According to Table V the MG revenue from the market participation, would be $6,179.183. This revenue is due to selling the power to the main grid. The generation cost regarding to case 2 has been increased about 66.5% in comparison with the case study 1. The excess generated power will be sold to the main grid which will cause about $2,424.654 overall profit to the MG. Figure 6 shows the produced power of units at the scheduling horizon. It should be mentioned that the expected values for the sold and bought energy as well as wind power generations are illustrated in the Fig. 6, due to their stochastic nature. According to Fig. 6 the wind power generators will produce power in their maximum capacity. Therefore, the excess generated power of units will be sold to the market. Table V and Fig. 6 shows that the MG will supply energy from the main grid only for a few hours of the day, which is as a result of low operation cost of CHP units, in comparison with the market price. Figure 7 shows the generated heat results of CHP units and boiler unit. According to Fig. 7 the boiler unit will not take part in supplying the heat demand due to its high cost function, in comparison with the CHP units.

In this case another study has been investigated in order to give an intuition about the deterministic and stochastic schedulings. In order to scrutinize this study three methods have been utilized: i) Resource problem (RP): The resource problem also known as stochastic solution (SS) is achieved by explicitly envisaging all of the scenarios. The value of objective function of this solution is called RP.

ii) Expected value (EV): The expected value of a

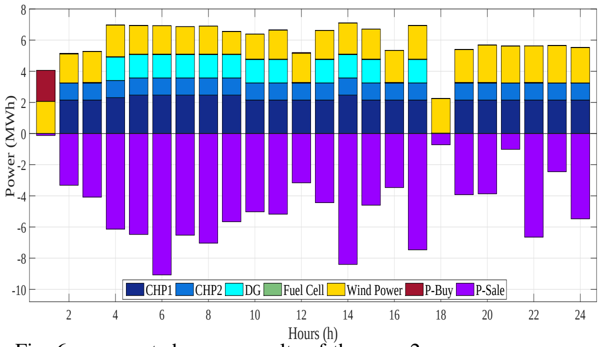

Fig. 6. generated power results of the case 2.

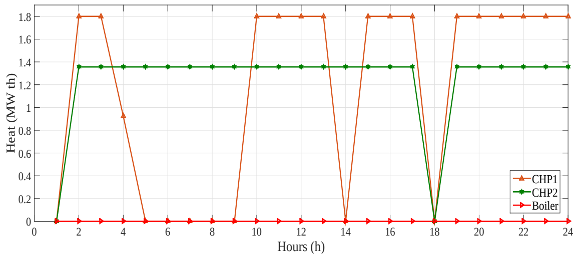

Fig. 7. generated heat results of the case 2.

problem can be achieved by considering the expected value of all random parameters. The objective function value corresponding to deterministic problem indicates the EV solution.

iii) Expected outcome of using the expected value (EEV): The solution of this case is obtained by fixing the decisions of the first stage variables with the results achieved from the deterministic solution, and solving the stochastic program by considering all scenarios. It should be mentioned that, this solution presents the true profit of the deterministic solution. The value of stochastic solution (VSS) is computed by subtracting the solution of RP from the EEV as follows [43]:

$$VSS = RP - EEV \tag{54}$$

The comparison of obtained best compromise solution using the three mentioned methods is presented in Table VI. The VSS for profit is equal to $220.654 which indicates the extra profit of using a stochastic model instead of the deterministic method. This observation is due to the RP and EEV methods difference in solving the problem. The EEV method considers the scenarios after deciding about first stage variables, however, the RP method considers all scenarios while solving the problem and deciding about first stage variables as well as second stage variables.

3) Case study 3: Impact of DR program on the MG scheduling: This case studies the scheduling problem without considering DR program, in order to illustrate the effect of applying the proposed DR program in the CHP-based MG scheduling problem. Table V presents the results regarding to case 3. In comparison with the

TABLE VI
TOTAL PROFIT USING DIFFERENT UNCERTAINTY CONSIDERATION METHODS RELATED TO CASE 2.

Method	EV	RP	EEV
Total profit	$2,488.012	$2,424.654	$2,204.00

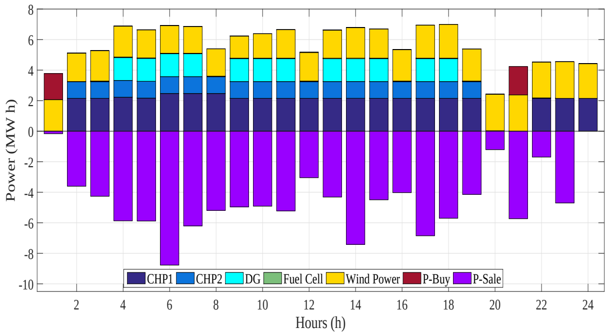

Fig. 8. generated power results of the case 3.

second case, the total profit has been decreased, however the production cost has decreased nevertheless. As obvious from Table V, the MG profit will be $2,186.1 that has decreased about 10% in comparison with the case which applies DR program. This decrement in the total profit value confirms the effectiveness of applying the proposed DR program in the CHP-based MG scheduling problem. Figure 8 depicts the generated power and provided energy from the grid. According to the Fig. 8 the provided energy from the grid is non zero only for a few hours of the day. In addition, according to the simulation results the boiler unit will produce the heat at hours 21:00 to 23:00. In spite of the CHP unit 1 power generation at hours 7:00 to 9:00, it will not generate heat , therefore, the CHP unit 2 and stored heat in the heat bffer tank are the only suppliers of heat demand at these hours.

V. CONCLUSION

This paper presented a stochastic programming framework for optimal scheduling of a CHP-based MG, comprising four types of thermal power generation units, two types of cogeneration units, energy storage systems, and demand response programs. In the optimal scheduling problem of a MG, the objective is maximizing total profit of MG, in the case of grid-connected operation mode, also, minimizing total cost of thermal and electrical energy supply in the case of islanded mode. In order to achieve this objective, DR program is implemented in the proposed framework. In addition, the CHP units with heat-power dual dependency characteristic is modeled using mixed-integer linear programming formulation in the MG scheduling problem. In the paper, the stochastic processes describing the price behavior in day-ahead market and the MGs power demand are modeled using SARIMA models. The weekly and daily seasonalities of MG load and market prices have been modeled in the scenario generation technique. The stochastic wind speed process is modeled using proposed scenario generation procedure which employs ARMA model. Moreover, in order to handle the large scale stochastic programming problem, fast backward scenario reduction technique has been implemented. The results show that the proposed model can cover the total electrical and thermal demands with respect to economic criteria. In addition, by implementing the DR program the total profit has been increased noticeably. According to the results of the case studies, although integrating DR programs will increase 3.1% of daily operation cost from $3,641.38 to $3,754.529, however, it will increase total profit more than 9.8% , up to $2,424.654, comparing to the base case (case without DR program) with total profit of $2,186.1. In addition, the case studies illustrated that by implementing the proposed framework the MG can obtain a meaningful profit in the grid-connected mode in comparison with the islanded-mode, as well as supplying total electrical and heat demand.

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