This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

Stochastic Modeling of Multienergy Carriers Dependencies in Smart Local Networks With Distributed Energy Resources

Nilufar Neyestani, *Student Member, IEEE*, Maziar Yazdani-Damavandi, *Student Member, IEEE*, Miadreza Shafie-khah, *Member, IEEE*, Gianfranco Chicco, *Senior Member, IEEE*, and João P. S. Catalão, *Senior Member, IEEE*

***Abstract*—In a multienergy system, there are different types of dependencies among the energy carriers. Internal dependencies refer to possible changes in the energy source in the presence of energy converters and storage, and are managed by the system operator through the control strategies applied to the equipment. External dependencies (EDs) are due to the choice of the energy supply according to customer preferences when alternative solutions are available. This paper introduces a new model of EDs within a multigeneration representation based on energy hubs. EDs are addressed through a stochastic model in order to take into account the possible uncertainty in the customers' decisions. This model is then used to introduce carrier-based demand response (DR) in which the user participates in DR programs aimed at promoting the shifting among different energy sources by preserving the service provided to the end users. The results obtained from the new model in deterministic and stochastic cases indicate the appropriateness and usefulness of the proposed approach.**

***Index Terms*—Carrier-based demand response (CBDR), distributed energy resources (DERs), energy shifting, internal and external dependency model, operational flexibility, smart multienergy system.**

NOMENCLATURE

Acronyms

AB	Auxiliary boiler.
CBDR	Carrier-based demand response.
CHP	Combined heat and power.
CS	Carrier share.
DER	Distributed energy resource.
DR	Demand response.
ED	External dependency.
HS	Heat storage.
PDF	Probability density function.

Subscripts

e	Electricity.
g	Natural gas.
h	Heat.
t	Time interval.
s	Scenario.
α, β, ω	Generic energy carriers.
D	Dependent output.
I	Independent output.

Superscripts

CB	Participating demand in a CBDR program.
dd	Demand dependency.
in	Input energy to the micro-multienergy system.
CS	Customer choice share.
n	Indicator of new matrix or variable.
o	Indicator of traditional matrix.
out	Indicator of the variables that determine the share of energy demand from input energy carriers.
r	Energy storage.
$r^{(+)}, r^{(-)}$	Energy storage charging and discharging.

Parameters and Variables

es, $\dot{\text{es}}$	Energy stored amount and variation.
Q, q	Heat energy.
$\dot{q}$	HS level difference in two consecutive time intervals.
L, l	Energy demand.
p	Energy input.
R	Maximum charge and discharge rate of HS.
v	Continuous variable determining the share of each energy element from input energy carriers or share of each carrier from dependent demand.
W, w	Electrical power.
x	Uncertain variables.
Γ, γ	Heat to power ratio.
η	Efficiency.

Manuscript received April 24, 2014; revised August 26, 2014, January 15, 2015, and March 11, 2015; accepted April 13, 2015. This work was supported in part by FEDER funds (European Union) through COMPETE, in part by the Portuguese funds through FCT under References FCOMP-01-0124-FEDER-020282 (PTDC/EEA-EEL/118519/2010) and UID/CEC/50021/2013, and in part by the EU Seventh Framework Programme FP7/2007–2013 under Grant 309048 (Project SiNGULAR). Paper no. TSG-00346-2014.

N. Neyestani, M. Yazdani-Damavandi, M. Shafie-khah, and J. P. S. Catalão are with the University of Beira Interior, Covilha 6201-001, Portugal, and also with INESC-ID/IST, University of Lisbon, Lisbon 1000-029, Portugal (e-mail: catalao@ubi.pt).

G. Chicco is with the Energy Department, Power, and Energy Systems Unit, Politecnico di Torino, Torino 10129, Italy.

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TSG.2015.2423552

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

π Input energy carrier price.
ρ Probability.
μ Expected (mean) value of uncertain variables.
σ Standard deviation.
$\dot{\mathbf{e}}_\mathbf{s}$ (Column vector) changes in stored energy.
$\mathbf{p}$ (Column vector) input energy.
$\boldsymbol{\lambda}$ (Column vector) output energy.
$\mathbf{C}$ Coupling matrix.
$\mathbf{S}$ Storage coupling matrix.

Remark 1: An underlined (overlined) variable is used to represent the minimum (maximum) value of that variable.

Remark 2: Capital letters denote parameters and small ones denote variables.

Remark 3: f is the function of the considered variables.

I. Introduction

A. Motivation

THE INTRODUCTION of distributed energy resources (DERs) is taking a significant part in forwarding the sustainable development and hedging the problems occurring to future energy portfolios [1]. Being co-related to both loads and energy supply system, DERs can increase the opportunities to enhance the services offered to loads as well as taking more benefits of loss reduction by changing the way of power transfer [2]. As the penetration of technology grows among the devices that are used by end users, the demand side will be more capable and eager to participate in advancing the sustainable development. This process does not only help the progress of sustainable development, but also will bring more technical and economic advantages to end users.

However, utilization of these resources for achieving the sustainable development objectives necessitates the employment of smart grids in order to convert this potential possibility into actual solutions [3]. Facilitating the bi-directional relation between the user and the system operator makes it possible to utilize and operate DERs at different levels [4]. In this regard, the technological development and commercialization is increasing the availability of technologies such as small-scale CHP units and energy storage systems, which are introduced in distributed multigeneration (DMG) systems [5] to enhance the flexibility of serving a multienergy demand.

B. Literature Review

Various researches have been conducted about modeling and studying multienergy networks. Geidl *et al.* [6] proposed an integrated model for this kind of networks as an energy hub. Following this model, further studies and model developments have been surveyed, some of which have been summarized in Table I [6]–[35].

As shown in Table I, the references proposing energy hub models consider the partitioning of the multienergy system into two parts: 1) energy hubs; and 2) interconnectors. In these studies, the input and output energy carriers are considered individually.

TABLE I
Research Domains in Energy Hub System Studies

Research Domain	References	Description
Modeling and Optimal Energy Flow	[6]-[13]	Multi energy system is decomposed into two parts, energy hubs and interconnectors. The energy flow is investigated in both parts and integrated system.
Operation	[14]-[19]	Energy hub system operation considering energy carriers price and operation objectives is surveyed.
Planning and Investment Portfolio	[20]-[25]	Future energy system characteristics are determined and the planning procedure is designed.
Reliability and Security Studies	[26]-[30]	Reliability analysis and security assessment (cascading failure case) are investigated in various operation conditions and the impact of storages is considered.
Modeling of DER Technologies in Energy Hub System	[25], [31]-[35]	The role of PHEVs, DRs and wind turbines are modeled in energy hub system studies.

Regarding the modeling of the system, two main approaches have been previously adopted for comparing the solutions in multienergy networks.

The first group of researchers does not consider the demand side energy converters and models the network just before end use [6], [36]. The second group [19] models networks with energy converters at the end service level with high resolution, but in a very limited area such as a household.

In [36], a matrix model is proposed considering the same input and output vectors, showing how the models of the individual components can be aggregated to obtain the matrix model of the overall energy system. However, as the penetration of smart technologies grows in the system, the input and output vectors of the multienergy system will no longer be only composed of individual components [37]. In fact, various devices that can use different sources of energy for producing the same output service are employed by the end users.

Then, the output of the multienergy system will depend on these devices and the consumers' behavior on utilizing them. As a result, the effects of the consumers' behavior and the randomness associated to it have to be considered.

C. Problem Description and Contributions

This paper addresses the presence of the demand that can be supplied by various types of carriers, its effects on multienergy system modeling, and the exploitation of this type of demand within DR programs.

The basic concept considered in this paper is the one of *dependent demand*, that is, the demand referring to a specific service that can be covered by producing the related energy from different energy carriers. Examples of dependent demand can be indicated for energy systems of different size. In a simple case, the required heat of a typical house can be provided both by electrical and gas-fired heaters. The amount of gas or electricity required for the system depends on the user's choice of the energy carrier in providing its dependent demand. Similar situations may occur in larger buildings where more persons are living or operating, by considering the possibility

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

of obtaining services such as water heating, cooking, and air conditioning (with multiple points in which these services can be provided) from multiple energy carriers, leaving the end user the possibility of choosing the energy carrier to supply the dependent demand.

The possibility of providing services from various energy carriers is linked to the availability of different energy supply systems in the same area. This may seem impractical. However, there are situations in which this kind of solutions are present or expected in real-life situations. The most remarkable situation is the one in which the trend of energy supply in the region in which the demand is located is changing, for instance because the energy mix in that region has been varied by the availability of new energy sources (e.g., from renewable generation) or by obsolescence of the existing power plants that are replaced with new technologies using different energy carriers. This situation includes for example either change from power to gas (leading to "less-electric" demand, or from gas to power (leading to "more electric" demand) [38]. In these cases, the end users can be induced to change the technologies they are using. However, the end users could decide to keep the previously used technology and integrate them with a new one, with the prospect of possible usage of both technologies depending on their convenience, e.g., to manage the case of shortage of energy supply for one energy carrier or large price fluctuations for the energy carriers that can be used to provide the same service. The demand side can change the source of providing the same service based on each energy carrier's price, availability of technologies, or only its preference. In the presence of multiple end users acting on the same system, the customer choices can be applied in a random way, so that the dependent demand becomes stochastic.

The system operator can set up DR programs aimed at taking benefits from this flexibility to manage the dispatch of the energy carriers within the multienergy system. In [39], it is shown how DR can be activated to promote changes in the demand behavior in response to changes occurred as exogenous stimuli (supply carriers' price variations, or specific incentives), defining a procedure according to which no customer suffers from these changes. In [40], it is indicated how DMG can be exploited to reduce the electricity input from the upstream network. This possibility is discussed on the basis of the concept of electricity shifting potential in the prospect of using DMG to provide real-time DR. In [41], an electric heat pump is used to provide heating and cooling to a multienergy system, switching the heating/cooling from electric heat pump to another equipment as a DR program.

This paper considers that the dependent demand can be totally or partially made available by the end user to participate in specific DR programs. For this purpose, the following possibilities are defined for the dependent demand usage.

1) *Carrier Share (CS):* The user decides which energy carrier is used for the part of dependent demand that does not participate in DR programs.
2) *Carrier-Based DR (CBDR):* The user decides which energy carrier is used for the part of dependent demand that participates in DR programs. This means that, if needed, the system operator can send a signal to the customer so that the energy carrier for providing a specific service will be shifted to another one, instead of just shedding the service.

CBDR is applied to change the type of energy supply from different sources (including energy storage) in such a way that the service is provided, and hence the level of comfort and customers' satisfaction remain unchanged. It is assumed that on the demand side the technology of having dependent demand does exist. If the end user agrees to participate in the CBDR program, whenever the operator needs less/more usage on one energy carrier, it sends a signal to the end users to change the source of energy carrier (from one type to another) by an amount that does not affect the service provided. In practice, the network operator can communicate with the consumers to motivate them for changing their consumption pattern during time. Facilitating this communication also makes an opportunity for implementing various DR programs. Relating to the incentives and affected satisfaction of consumers in the DR process, the consumers' response to these programs can be different. One-way communication and sending signals for encouraging the participation of consumers in DR programs is already achievable [41]–[43].

In the light of the concepts indicated previously, the contributions of this paper are threefold.

1) Represent customer's choice in the multienergy system model to increase flexibility, by extending the matrix model of the multienergy system to incorporate the effects of dependent demand.
2) Extend the degrees of freedom for applying DR by proposing a CBDR program.
3) Assess the stochastic behavior of the demand side for selecting the carriers by means of implementing scenarios incorporating CBDR programs.

D. Paper Organization

The rest of this paper is organized as follows. In Section II, the dependent demand is categorized by identifying internal and external dependencies. In Section III, a comprehensive model is proposed for energy networks with multienergy system dependency. In Section IV, the modeling of a local energy network considering the EDs of the network and its stochastic operational model is determined. Section V discusses the uncertainty characterization of ED. Section VI explains the results of implementing the proposed model on a test system. The conclusion is presented in the last section.

II. Internal and External Dependencies

In a multienergy system, the dependencies can be divided in two main categories: 1) internal dependencies; and 2) EDs.

The internal dependencies refer to the relations between input and output energy carriers due to the presence of energy converters existing in the multienergy system and controlled by the system operator (for example, deciding the energy flows among multiple equipment belonging to a multigeneration system, on the basis of a specified control strategy or optimization objective [14], [36]).

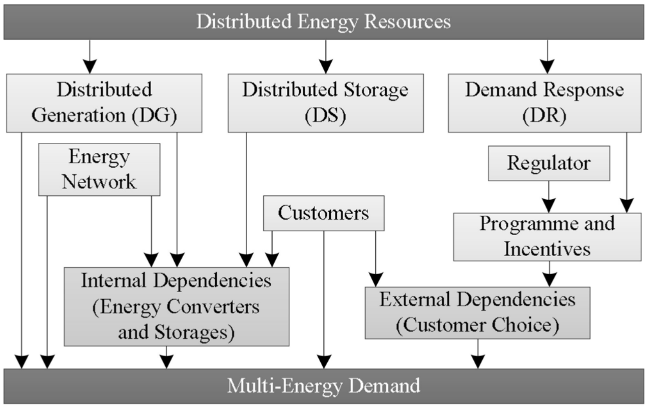

Fig. 1. Structure of DER supply and related dependencies in serving multienergy demand.

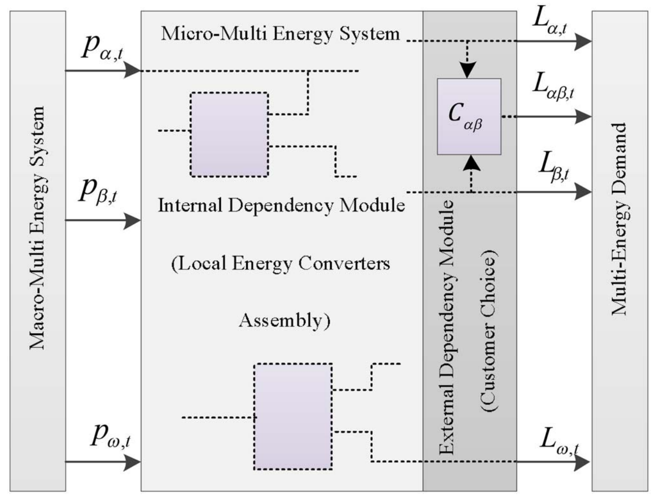

Fig. 2. Energy system comprehensive module considering internal dependencies and EDs.

Conversely, the EDs are mainly due to actions not depending on the network operator, which may have effects on the way the multienergy demand is served. These actions generally depend on the user's preferences triggered by DR programs and incentives established by the regulator.

The considerations of the EDs also depend on the penetration level of the distributed energy converters located at the user's side and directly activated by the customers for changing the energy supply (e.g., electrical and gas boilers for hot water production, and local management of storage).

The framework representing the relations of various elements in the multienergy system and the position of internal dependencies/EDs is shown in Fig. 1.

As the dependent demand causes an ED in the system, it will affect the conventional models used for the multienergy systems.

Two main references that have focused on modeling the dependencies are [6] and [44]. In these references, the dependency between carriers is considered through the coupling matrix.

Furthermore, Kienzle *et al.* [25] addressed the model of the external time dependency arising by modeling the stored heat demand as DR in a residential area.

However, the survey of the literature approaches shows that a structured view of the dependencies among the energy carriers, taking into account the role of the user and the related preferences, has not been provided yet. Hence, in this paper, the ED on the demand side is modeled as a specific module in the multienergy system, which has not been tested in previous studies, posing a new contribution. In addition, the stochastic nature of consumer preferences is addressed. This will bring higher levels of flexibility to the energy usage in the network, while reducing operation costs.

III. Comprehensive Energy System Model

Energy systems have a multilayer nature. A possible representation with three main layers is indicated in Fig. 2, namely, macro-multienergy system (referring to external energy systems and networks), micro-multienergy system (i.e., the local system under analysis), and multienergy demand.

The energy system analysis is carried out by assuming that the services requested by the user and the associated multienergy demands are known.

Looking at the multienergy system equipment, two main elements exist in the energy system model: 1) energy converters; and 2) energy storages. In this section, the matrix model for these elements is presented, highlighting the effects of the possible interdependencies among the energy carriers. The time scale used for the representation depends on the averaging time interval with which the data are available. Without loss of generality, the subscript t is used here to scan the time intervals.

Thereby, this model is efficient both on the operation timescale, provided that appropriate control or DR signals are available in a relatively short term (from minutes to hours) to change the equipment set point (thus affecting the internal dependencies) or to induce changes in the customers' preferences as EDs, and in long-term planning of local energy networks.

A. Energy Converter Model

In the classical energy hub model, the overall system is represented by a coupling matrix $\mathbf{C}$ that converts the input energy carriers, vector $\mathbf{p}$, e.g., natural gas, electricity, and district heating, into output energy services, vector $\boldsymbol{\lambda}$, like electricity, cooling and heating, and mechanical power

$$[\boldsymbol{\lambda}] = [\mathbf{C}]\left[\mathbf{p}\right]. \tag{1}$$

Based on Fig. 2, the expansion of (1) showing the relation between input and output carriers is modeled as

$$\begin{bmatrix} L_{\alpha,t} \\ L_{\beta,t} \\ \vdots \\ L_{\omega,t} \end{bmatrix} = \begin{bmatrix} C_{\alpha\alpha} & \cdots & C_{\alpha\omega} \\ C_{\beta\alpha} & \cdots & C_{\beta\omega} \\ \vdots & & \vdots \\ C_{\omega\alpha} & \cdots & C_{\omega\omega} \end{bmatrix} \begin{bmatrix} p_{\alpha,t} \\ p_{\beta,t} \\ \vdots \\ p_{\omega,t} \end{bmatrix}. \tag{2}$$

Each element of the matrix $\mathbf{C}$ denotes the conversion of one carrier into another and is composed of two categories of parameters: the first category includes coefficients depending on physical characteristics of the system and of the energy converters, such as the efficiencies (η_α).

The second category includes the decision variables, here denoted as weighted energy contribution variables ($v_{\alpha,t}$), which indicate the energy distribution among the energy converters in (3). In fact, these are continuous variables that determine the share of each energy carrier in the total energy demand. Only in very simple cases the decision variable can be considered as binary, representing a switch between two possible alternatives to supply the demand needed for a given service by using two energy carriers. Hence, the entries of the matrix $\mathbf{C}$ can be expressed as

$$C_{\alpha\beta} = f(v, \eta). \tag{3}$$

The classical model encompasses the presence of the internal dependencies referring to the energy CS among different equipment, in which the decision variables (e.g., the dispatch factors indicated in [6]), represent degrees of freedom to determine the energy flows in the multienergy system and can be set up as a result of optimization procedures run by considering specific objective functions [6], [38]. However, this model formulation does not include the representation of the customer choice affecting the energy carriers' usage. This representation is incorporated here in the ED module highlighted previously in Fig. 2.

The proposed extension of the model shows that, besides consuming a certain amount of each energy carrier at each time interval ($L_{\alpha,t}$, $L_{\beta,t}$, etc.), the multienergy demand has the ability to receive a defined amount of energy ($L_{\alpha\beta,t}$) from different carriers to supply the required service.

The weighted energy contributions depending on the customer preferences in the ED module are equivalent to the dispatch factors considered in the model representing the internal dependencies.

Dependency between outputs is added to the demand vector through one or more additional entries, which increase the number of rows of the coupling matrix (4). It should be noted that these added lines do not represent actual outputs, but virtually illustrate the dependency in output

$$\begin{bmatrix} L_{a,t} \\ L_{b,t} \\ \vdots \\ L_{\omega,t} \\ L_{\alpha\beta,t} \end{bmatrix} = \begin{bmatrix} C_{aa} & \cdots & C_{a\omega} \\ C_{ba} & \cdots & C_{b\omega} \\ \vdots & \vdots & \vdots \\ C_{\omega\alpha} & \cdots & C_{\omega\omega} \\ C_{\alpha\beta\alpha} & \cdots & C_{\alpha\beta\omega} \end{bmatrix} \begin{bmatrix} p_{\alpha,t} \\ p_{\beta,t} \\ \vdots \\ p_{\omega,t} \end{bmatrix}. \tag{4}$$

Hence, the output vector $\boldsymbol{\lambda}$ in the proposed model (column vector containing the terms $L_{\alpha,t}$, $L_{\beta,t}$, etc.) can be divided into two sections as in (5), with rows indicating independent output carriers ($\boldsymbol{\lambda}_I$) and rows introducing dependency in the output ($\boldsymbol{\lambda}_D$). The same approach can be performed on the coupling matrix. Therefore, the matrix model will have new rows that make it different with respect to the one used in [7] and [27]

$$[\boldsymbol{\lambda}] = \begin{bmatrix} \boldsymbol{\lambda}_I \\ \boldsymbol{\lambda}_D \end{bmatrix} = \begin{bmatrix} \mathbf{C}_I \\ \mathbf{C}_D \end{bmatrix} [\mathbf{p}] \tag{5}$$

where

$\mathbf{C}_I$ traditional coupling matrix that states the conversion of independent inputs into independent outputs;

$\mathbf{C}_D$ matrix showing the share of the independent inputs in providing dependent demand;

$\mathbf{p}$ column vector containing the input variables.

An application example is illustrated in Section III.

B. Energy Storage Model

As Arnold and Andersson [9] and Kienzle and Andersson [22] have explained, the role of energy storages can be modeled through some changes in the coupling matrix and the input energy vector. Regarding the EDs, the fact that the user can resort to individual storages causes the definition of an extended input vector ($\mathbf{p}_n$) with respect to the input vector $\mathbf{p}$ used in the case where no storage exists.

On the one hand, the amount of energy consumed from storages (vector $\dot{\mathbf{e}}_\mathbf{s}$) is added to the input vector. On the other hand, the coupling matrix of the storage ($\mathbf{S}$), which represents how changes in the amount of energy stored will affect the system output, is added to the total system coupling matrix. Hence, the combined model is shown

$$[\boldsymbol{\lambda}] = \begin{bmatrix} \mathbf{C} & -\mathbf{S} \end{bmatrix} \begin{bmatrix} \mathbf{p}_n \\ \dot{\mathbf{e}}_\mathbf{s} \end{bmatrix}. \tag{6}$$

In the modified model, $\dot{ES}$ is the change in the stored energy and can be computed from (7) and (8) by considering the charge/standby conditions or the discharge conditions

$$\dot{es}_{a,t} = es_{a,t} - es_{a,t-1} \tag{7}$$

$$\eta_\alpha^r = \begin{cases} \eta_\alpha^{r(+)}, & \text{if } \dot{ES}_{\alpha,t} \geq 0 \text{ (Charge/Standby)} \\ 1/\eta_\alpha^{r(-)}, & \text{if } \dot{ES}_{\alpha,t} < 0 \text{ (Discharge)}. \end{cases} \tag{8}$$

By decomposing the storage coupling matrix $\mathbf{S}$ into its components $\mathbf{S}_I$, showing changes of independent output versus changes in the stored energy, and $\mathbf{S}_D$, showing changes of dependent output versus changes in the stored energy, the matrix formulation becomes

$$\begin{bmatrix} \boldsymbol{\lambda}_I \\ \boldsymbol{\lambda}_D \end{bmatrix} = \begin{bmatrix} \mathbf{C}_I & -\mathbf{S}_I \\ \mathbf{C}_D & -\mathbf{S}_D \end{bmatrix} \begin{bmatrix} \mathbf{p}_n \\ \dot{\mathbf{e}}_\mathbf{s} \end{bmatrix}. \tag{9}$$

IV. Local Energy System Stochastic Operational Model

In order to show an application of the proposed model, a typical local network model is shown in Fig. 3, with CHP unit, AB, and HS.

The input carriers of the system are electricity and gas, while the output carriers are electricity, gas, and heat. The ED between gas and electricity carriers in this network is considered through the demand dependency module ED in the output (with output variable $L_{eg,t}$). The EDs due to the behavior of the consumers are not deterministic; therefore, the related uncertain variables are considered in a scenario-based stochastic model, in which the subscript s represents the scenarios.

The typical scenarios considered are the CS indicated in Section I-C when no DR program is defined, and the CBDR scenarios considering the shifting between energy carriers in order to maintain the customers' satisfaction through the

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

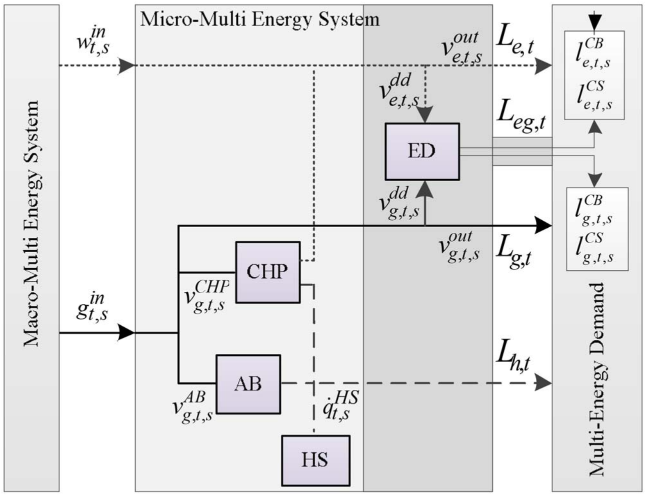

Fig. 3. Typical local energy network model considering the energy carriers dependency.

definition of DR programs. It is assumed that some customers agree that their demand would be participating in this type of DR.

CS is based on the user's decision on which multienergy carrier has to be used for the part of dependent demand that does not participate in CBDR programs, while the remaining part of the dependent demand is available to contribute to CBDR.

The considerations on uncertainty and the details of the scenarios are described in Section V. The energy dispatch between the various elements is described by using the weighted energy contribution variables v, for both internal and EDs. The links among the weighted energy contribution variables are indicated hereafter.

Based on the proposed model in the previous section, the mathematical model of this network is shown

$$\begin{bmatrix} v^{\text{out}}_{e,t,s} & v^{\text{CHP}}_{g,t,s}\,\eta^{\text{CHP}}_{e}\,v^{\text{out}}_{e,t,s} & 0 \\ 0 & v^{\text{CHP}}_{g,t,s}\,\eta^{\text{CHP}}_{h} + v^{\text{AB}}_{g,t,s}\,\eta^{\text{AB}}_{h} & 1/\eta^{r}_{e} \\ 0 & v^{\text{out}}_{g,t,s} & 0 \\ v^{\text{dd}}_{e,t,s} & v^{\text{dd}}_{g,t,s} + v^{\text{dd}}_{e,t,s}\,v^{\text{CHP}}_{g,t,s}\,\eta^{\text{CHP}}_{e} & 0 \end{bmatrix} \begin{bmatrix} w^{\text{in}}_{t,s} \\ g^{\text{in}}_{t,s} \\ \dot{q}^{\text{HS}}_{t,s} \end{bmatrix} = \begin{bmatrix} L_{e,t} \\ L_{h,t} \\ L_{g,t} \\ L_{eg,t} \end{bmatrix}. \tag{10}$$

It should be noted that in this paper the model is studied in steady state, namely, the time step of analysis is considered to be sufficiently long to assume that all the equipment (also the slower thermal elements on the demand side) have concluded their transient period and have reached their steady state. As a result, the dynamics on the demand side can be neglected.

The local energy network is assumed to consist of small residential smart buildings, in which indicatively the minimum time step for analyzing successive steady-state conditions can be of the order of minutes. In any case, the time step used for the calculations in this paper is longer (hours), so the representation of the equipment dynamics is not needed.

A. Objective Function

The objective function in operating this system is to minimize the costs of providing the required amount of gas energy input $g_{t,s}$ and electrical energy input $w_{t,s}$, taking into account the costs per unit of energy $\pi_{e,t}$ and $\pi_{g,t}$ for electricity and gas, respectively.

This model has been formulated to obtain the total expected cost for various scenarios of dependency in the system

$$\text{Min} \quad \sum_{s} \rho_s \sum_{\alpha} \sum_{t} \left(w_{t,s}\,\pi_{e,t} + g_{t,s}\,\pi_{g,t} \right) \tag{11}$$

with

$$\rho_s = \left\{ \rho^{\text{CB}}_{s}, \rho^{\text{CS}}_{s} \right\}$$

where ρ^{CB}_{s} and ρ^{CS}_{s} are respectively the probabilities of being in the CBDR or in the CS scenarios. The details of the scenarios are explained in Section V.

B. Operational Constraints

The constraints are generally expressed in terms of capacity. As such, in order to check the constraints it is needed to express the average power values in the relevant time subinterval.

Let us consider for each hour the number n_τ of uniformly spaced time subintervals (e.g., $n_t = 4$ for 15 min subintervals) [28].

Hence, the energy input corresponds to the average power as in

$$w_{t,s} = w_{t,s}/n_t,\; g_{t,s} = g_{t,s}/n_t. \tag{12}$$

The same relation holds between any average power and energy quantities. The constraints for system operation are formulated as follows.

1) *Input Carriers Constraints:* Each energy carrier has a supply limit that may be due to the power amount from the supply source or power transmission limits

$$0 \le w_{t,s} \le \overline{W}^{\text{in}},\;\; 0 \le g_{t,s} \le \overline{G}^{\text{in}}. \tag{13}$$

2) *Operational Constraints of the CHP Unit:* Regarding manufacturing characteristics of the CHP unit, they face limits in the amount of electrical power output $w^{\text{CHP}}_{t,s}$ or heat power output $q^{\text{CHP}}_{t,s}$. Furthermore, the CHP unit should be operated in the allowed heat to power ratio zone

$$\underline{W}^{\text{CHP}} \le w^{\text{CHP}}_{t,s} \le \overline{W}^{\text{CHP}} \tag{14}$$

$$\underline{Q}^{\text{CHP}} \le q^{\text{CHP}}_{t,s} \le \overline{Q}^{\text{CHP}} \tag{15}$$

$$\gamma^{\text{CHP}}_{t,s} = \frac{q^{\text{CHP}}_{t,s}}{w^{\text{CHP}}_{t,s}} \tag{16}$$

$$\underline{\Gamma}^{\text{CHP}} \le \gamma^{\text{CHP}}_{t,s} \le \overline{\Gamma}^{\text{CHP}}. \tag{17}$$

3) *Operational Constraints of the Auxiliary Boiler:* Heat output from the AB has some capacity limits

$$\underline{Q}^{\text{AB}} \le q^{\text{AB}}_{t,s} \le \overline{Q}^{\text{AB}}. \tag{18}$$

4) *Operational Constraints of Heat Storage:*

$$\left| \dot{q}^{\text{HS}}_{t,s} \right| \le R^{\text{HS}}_{h} \tag{19}$$

$$\underline{Q}^{\text{HS}} \le q^{\text{HS}}_{t,s} \le \overline{Q}^{\text{HS}}. \tag{20}$$

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

5) *Constraints on the Weighted Energy Contribution Variables:*

$$0 \leq v \leq 1 \text{ for all weighted energy contribution variables} \tag{21}$$

$$v_{e,t,s}^{\text{dd}} + v_{e,t,s}^{\text{out}} = 1 \tag{22}$$

$$v_{g,t,s}^{\text{CHP}} + v_{g,t,s}^{\text{AB}} + v_{g,t,s}^{\text{dd}} + v_{g,t,s}^{\text{out}} = 1. \tag{23}$$

C. Model of External Dependency

As shown in the proposed model, the EDs are modeled in a block added to the rest of the micro-multienergy system model. In fact, this block is the interface between the micro-multienergy system and the output demand. However, in the proposed model, the dependency that actually happens on the demand side is modeled as a part of the micro-multienergy system. The block is added as a module in the model (Fig. 3). It should be noted that this module does not give a physical outcome, but it helps the operator of a multienergy system to have an insight from possible customers' choice of carriers. In a real network, this module can have outputs such as data or information signals that are sent to the operator 24 h before the operation day. Nevertheless, in this paper, the mathematical model for investigating the compatibility of the model is presented. Based on these explanations, the dependency module demonstrates that part of the multienergy demand can utilize both electricity and gas carriers to provide the required service. In order to deal with the dependency between the carriers in the system model, two weighted energy contribution variables are used, namely, $v_{e,t,s}^{\text{dd}}$ and $v_{g,t,s}^{\text{dd}}$, stating the share of dependent energy demand in the output of each carrier (electricity and gas, respectively)

$$f\left(v_{e,t,s}^{\text{dd}}, v_{g,t,s}^{\text{dd}}\right) = L_{eg,t}. \tag{24}$$

In (24), it is shown that the output dependent demand is a function of the variables of the two carriers (electricity and gas). The ED variables illustrate the dependent demand's share in usage of each carrier. Thus, it is necessary to balance them with some coefficients and then exploit them in the model.

The following new weighted energy contribution variables in the output show the share of each carrier in demand provision:

$$v_{e,t,s}^{\text{dd},n} = \left(\frac{w_{t,s}^{\text{in}} + g_{t,s}^{\text{in}}\, v_{g,t,s}^{\text{CHP}}\, \eta_e^{\text{CHP}}}{L_{eg,t}}\right) v_{e,t,s}^{\text{dd}} \tag{25}$$

$$v_{g,t,s}^{\text{dd},n} = \left(\frac{w_{t,s}^{\text{in}}}{L_{eg,t}}\right) v_{g,t,s}^{\text{dd}}. \tag{26}$$

As it is shown in (25) and (26), a new variable is defined to determine the share of dependent demand from electricity and gas, respectively. These equations show the share of dependent demand from the total input energy carriers. In other words, $v_{e,t,s}^{\text{dd},n}$ shows what amount of dependent demand is served by electricity. The same can be interpreted for $v_{g,t,s}^{\text{dd},n}$. Besides, these new variables are used to avoid the multiplication of weighted energy contributions and make the problem linear with respect to the decision variables.

Furthermore, it is clear that there is some equipment that enables the possibility of dependent demand. However, the equipment that has shares on energy contribution of the EDs is not ideal, and may waste some part of energy through the energy conversion process. Therefore, (27) represents the limit on the amount of weighted energy contribution variables depending on this block. This will ensure that the amount of energy that is assigned to each carrier is obtainable by the related equipment

$$v_{e,t,s}^{\text{dd},n} + v_{g,t,s}^{\text{dd},n} \geq 1. \tag{27}$$

V. Uncertainty Characterization of Internal and External Dependencies

The consumers' behavior for utilizing the mentioned dependencies is uncertain from the operator's point of view. Therefore, a scenario-based approach is adopted to characterize this behavior.

This section describes the model of the uncertainties on CBDR and energy carriers share.

A. Uncertainty of Carrier-Based Demand Response

Let us assume that the local energy network operator can send signals at each hour to its consumers to inform them on the desirable energy dispatch. The consumers can respond to this request based on economic and social behavior. One of the main stimuli that motivate consumers to participate in CBDR programs is the presence of incentives that can be based on price signals.

Some reports (see [45], [46]) have focused on modeling the customers' response during a DR event and obtaining the DR baseline error/accuracy.

Customers' response uncertainty refers to the percentage of consumers who participate in CBDR programs. In other words, consumers' CBDR acceptance is the main source of uncertainty considered in the ED modeling.

In this paper, a scenario-based approach is utilized to investigate the effect of the customers' response uncertainty on the operator's behavior.

Another important uncertainty regards the consumers who do not participate in CBDR programs, thus their demand is individually controlled, contributing to the terms referring to the internal dependency.

This uncertainty represents the probabilistic nature of consumers' behavior to select the carriers for supplying their own demand (Fig. 4).

Equations (28)–(33) represent the share of each carrier for providing CBDR and individually controlled demand

$$l_{eg,t,s}^{\text{CB}} = L_{eg,t}\, v_{t,s}^{\text{CB}} \tag{28}$$

where $v_{t,s}^{\text{CB}}$ represents the variable indicating the customers that agree to participate in CBDR. Hence, $l_{eg,t,s}^{\text{CB}}$ determines the part of dependent demand that takes part in CBDR.

The share of electricity and gas demand from total dependent demand is expressed as

$$l_{eg,t,s}^{\text{CB}}\, v_{e,t,s}^{\text{dd},n} = l_{e,t,s}^{\text{CB}} \tag{29}$$

$$l_{eg,t,s}^{\text{CB}}\, v_{g,t,s}^{\text{dd},n} = l_{g,t,s}^{\text{CB}}. \tag{30}$$

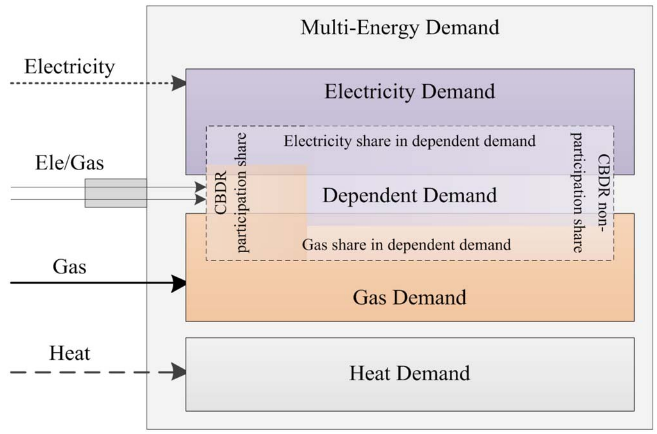

Fig. 4. Share of demand participation variables in dependent demand.

The choice of the customers who do not participate in CBDR from electricity and gas (that is, the users with CS dependent demand) is represented in the following equations, the variables $v_{e,t,s}^{\mathrm{CS}}$ and $v_{g,t,s}^{\mathrm{CS}}$ represent the share of electricity and gas, respectively

$$\left(L_{eg,t} - l_{eg,t,s}^{\mathrm{CB}}\right) v_{e,t,s}^{\mathrm{CS}} = l_{e,t,s}^{\mathrm{CS}} \tag{31}$$

$$\left(L_{eg,t} - l_{eg,t,s}^{\mathrm{CB}}\right) v_{g,t,s}^{\mathrm{CS}} = l_{g,t,s}^{\mathrm{CS}} \tag{32}$$

$$v_{e,t,s}^{\mathrm{CS}} + v_{g,t,s}^{\mathrm{CS}} \geq 1. \tag{33}$$

In addition, the amount of dependent demand in the study (demand dependency percentage) is calculated through the following equation:

$$\mathrm{dd}\% = \frac{L_{eg,t}}{\bar{L}_{eg,t}}. \tag{34}$$

B. Modeling the Uncertainties of CBDR and Carrier Share

The model of the local energy system should estimate the uncertain parameters of probabilistic consumers' behavior by past statistics data.

To create appropriate scenarios to model the mentioned uncertainties, several methods based on time-series (see [47]), artificial intelligence and evolutionary algorithms (see [48]) can be utilized.

In this paper, the uncertainties are modeled as multiple different scenarios. Then, a scenario-based stochastic programming approach is employed to handle uncertainties. The scenario-based stochastic programing is an efficient tool to find optimal decisions in problems involving uncertainty. When it comes to make decisions under uncertainty using stochastic programming, the building of scenario sets that properly represent the uncertain input parameters constitutes a preliminary task of utmost importance. In reality, the optimal decisions derived from stochastic programming models may be indeed remarkably sensitive to the scenario characteristics of uncertain data. For this reason, a large number of researches have been accomplished to design efficient scenario generation methods. A brief description of the most relevant methods is presented in [49].

However, the generation of a huge number of scenarios may render the underlying optimization problem intractable. Therefore, it is necessary to consider a limited subset of scenarios without losing the generality of the original set. Scenario reduction techniques can reduce the number of scenarios effectively [50], [51]. The probabilistic behavior of customers has caused the operator to face plenty of uncertainties in order to participate effectively in the market. Each customer behaves differently because of social and economic concerns. Therefore, each individual behavior will be different from others. In this paper, two sets of uncertainty are considered, regarding the customers' behavior. The first set is the uncertainty of customers' response to participate in a CBDR program, and the second set is the uncertainty of selecting the different carriers by the customers.

In order to generate scenarios with the mentioned uncertain variables, the normal distribution has been utilized, with PDF

$$f(x, \mu, \sigma) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{35}$$

where μ and σ represent the mean value and the standard deviation, respectively.

In other words, it is assumed that the uncertain variables have normal deviations around their mean values. On this basis, different realizations of CBDR and CS are independently modeled by employing a scenario generation process based on roulette wheel mechanism [52].

For the sake of fair comparison, it is assumed that μ is equal to its amount in the deterministic case and different values of σ have been considered.

VI. Numerical Results

For assessing the effectiveness of the proposed model, numerical results have been developed. As the internal dependency has been investigated in prior researches (see [19] and [36]), the numerical results presented here focus on the EDs.

The nonlinear formulation presented in this paper has been linearized as indicated in Section IV-C and modeled in such a way to be solved by using mixed integer linear programming with the CPLEX 12 GAMS solver.

The local energy network under study in this paper consists of CHP unit, AB, and HS. Inputs of this system are gas and electricity carriers, while the outputs are electricity, gas, and heat. Detailed information on these elements is provided in the Appendix, Table II.

The illustration of the results is organized in two sections. Section VI-A addresses the impact of the dependency existing in the proposed operational model of the multienergy system. Section VI-B shows and compares the results of stochastic models (representing the uncertainty in customers' choices) and deterministic models.

All the studies in this paper are first implemented on a base case where the amount of dependent demand is assumed to be zero ($l_{eg,t} = 0$). Then, in each step the level of dependency is increased.

However, it is assumed that the total amount of energy that the customers require remains equal in all steps. As a result,

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

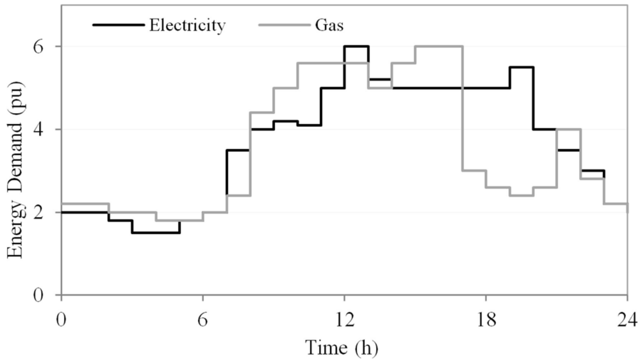

Fig. 5. Energy carriers demand data in the operation time horizon.

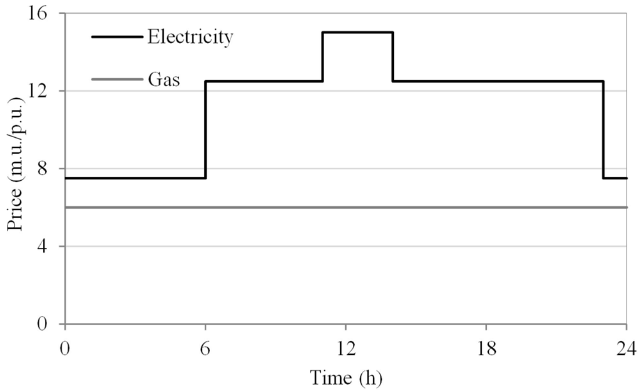

Fig. 6. Energy carriers price data in the operation time horizon.

the total amount of independent usage of electricity and gas has to be reduced. This reduction is conducted based on the efficiency of electricity and gas production elements in the system.

The information about local energy consumption in the base case and input energy carrier prices is indicated in Figs. 5 and 6. In this paper, the hot water consumption is considered as the ED that can be supplied by both gas-fired and electrical heaters. The numerical amount of dependency is considered like energy and is expressed in per unit (p.u.).

The heat demand data is depicted in Fig. 7. The relation between electricity and gas carrier weighted energy contribution variable in the dependent output of these two carriers is shown

$$\eta_e^{\mathrm{dd}} v_{e,t,s}^{\mathrm{dd},n} + \eta_g^{\mathrm{dd}} v_{g,t,s}^{\mathrm{dd},n} = 1 \tag{36}$$

where η_e^{dd} and η_g^{dd} are the efficiencies of the electrical and the gas-fired water heaters, respectively. The typical amounts considered for η_e^{dd} and η_g^{dd} are 0.9 and 0.6, respectively, based on [53]. Furthermore, the typical amounts of $v_{e,t,s}^{\mathrm{CS}}$ and $v_{g,t,s}^{\mathrm{CS}}$ are 0.26 and 0.74, respectively, based on [54].

In these studies, it is assumed that the system operator enables CBDR by controlling the gas and electricity dependent consumption. This can be achieved by sending one-way communication signals to the multienergy demand, taking advantage of the flexibility brought through this model.

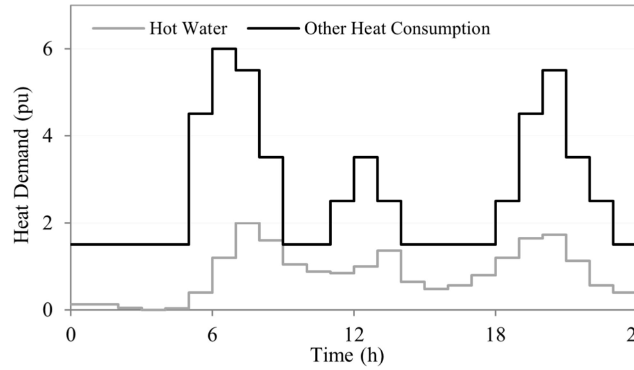

Fig. 7. Heat demand data in the operation time horizon.

A. Case I: The Operational Model Study

The first case study regards the impact of dependency and related CBDR programs in the network.

The aim is to investigate how the cost of the system and the energy dispatch between the carriers are affected by the dependency existing in the multienergy demand.

Various levels of hot water usage as dependent power in the output are considered ($l_{eg,t}$ varies from 0% up to 100% by intervals of 5%). In addition, five different values for the efficiency η_g^{dd} are assumed, while the efficiency of electricity η_e^{dd} is considered to be fixed.

For generating these cases, first, the total amount of the gas and electricity output from the local energy network to the multienergy demand are set up to specific values.

Then, as it is assumed that the total amount of output does not change, when the level of dependency increases, part of the previous demand of a carrier does not exist anymore and will be replaced by another carrier.

The corresponding demand amount is reduced from the original carrier and is added to the so-called dependency. The energy carriers are adjusted on the basis of the typical output share and efficiency of energy converters. For example, the gas and electricity shares are adjusted based on predetermined η_e^{dd} and η_g^{dd}. Furthermore, the total share of ED is considered for the CBDR program ($l_{t,s}^{\mathrm{CB}} = L_{eg,t}$).

Fig. 8 shows the total system cost versus gas-fired heater efficiency for various levels of the demand dependency percentage indicated in (34). When the output dependency increases with the same η_e^{dd}, the operational flexibility increases, resulting in lower system operation cost.

Conversely, for the same percentage of dependency when η_e^{dd} changes, the costs reach a maximum amount and then gradually decrease. The reason is that, as the output energy amount of local energy network remains constant, by reducing the gas energy converters' efficiency the system will provide more dependent demand through the electricity carrier. This means that up to a certain point, the operator of the micro-multienergy system still can manage to keep the balance between the total system cost and gas energy carrier's consumption, but after that it is better for the operator to exchange the carrier to another one, electricity in this case.

With relatively low efficiency of gas energy converters, the demand requirements can be achieved by taking the benefits

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

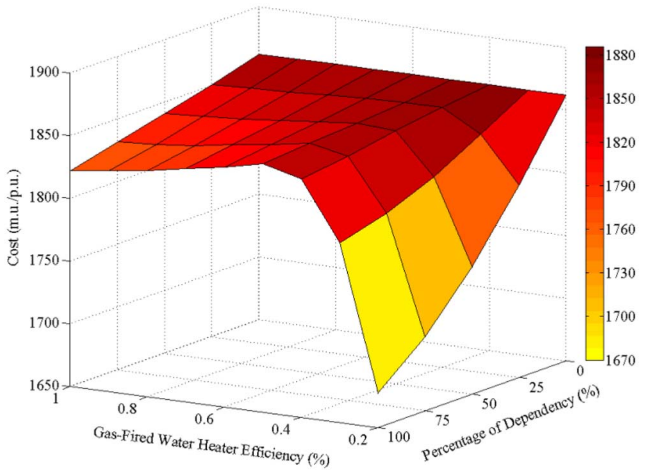

Fig. 8. System operation cost based on demand dependency percentage for different water heater efficiencies.

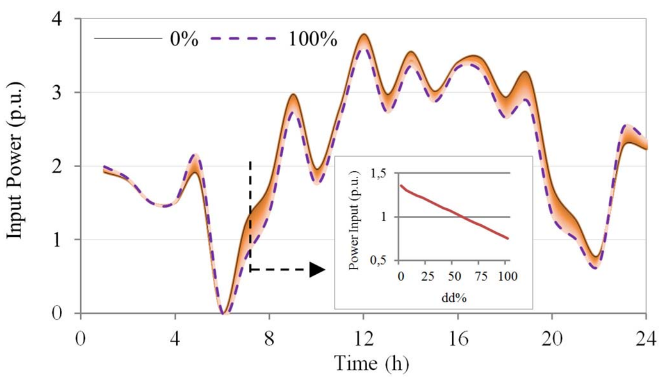

Fig. 9. Evolution of the electricity input for demand dependency percentage from 0% to 100%, with $\eta_g^{\mathrm{dd}} = 0.6$. Inset: zoomed-in view for hour 7 A.M.

of using less electricity with higher efficiency than the gas carrier and in a total view reducing the system operation cost. In other words, when the efficiency of an energy carrier converter on the demand side is too low compared to other carriers in the micro-multienergy system, it is better to change the source of dependent demand to another carrier that produces the required output with higher efficiency.

In general, this case study determines that more proficiency occurs when the micro-multienergy system and multienergy demands efficiencies are not close to each other. In this condition, the coordinated decision making between micro-multienergy system and multienergy demand will decrease the system's operational cost. The proposed ED model enables the quantification of the operational costs in different conditions.

Figs. 9 and 10 depict the amount of input electricity and gas carriers when $\eta_g^{\mathrm{dd}} = 0.6$ for various levels of dependency. In these figures, the dependency level is shown for 0% and 100%. The density of the colored region appearing between the 0% and 100% limits indicates that the input quantities change when the dependency level varies. The zoomed-in views included in the figures indicate the corresponding type of variation of the input quantities at a specific hour (7 A.M.).

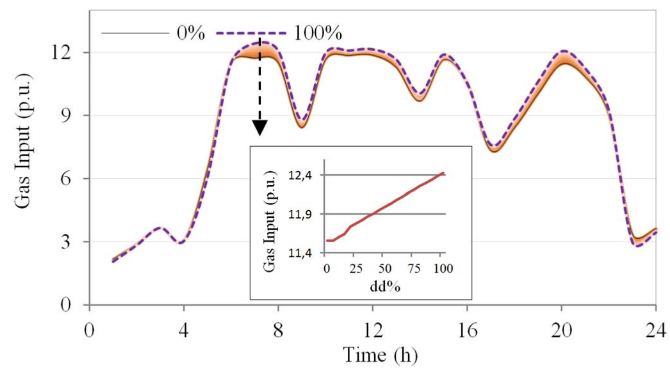

Fig. 10. Evolution of the gas input for demand dependency percentage from 0% to 100%, with $\eta_g^{\mathrm{dd}} = 0.6$. Inset: zoomed-in view for hour 7 A.M.

As it is shown in Figs. 9 and 10 at the specific hour 7 A.M., the variation of power and gas input versus increasing variation of demand dependency follows an opposite manner.

With increase in dependency percentage the consumption of electricity decreases while the consumption of gas has an increasing trend. The reason is that during hours 6–22 the average electricity price is high; therefore, the system operator prefers to provide the dependent energy amount through gas carrier rather than electricity, which also results in the reduction of the total operation cost. On the other hand, during hours 1–5, 23, and 24, when electricity price is lower, by increasing the level of dependency the tendency for electricity carrier consumption increases, while gas consumption shall decrease.

B. Case II: Comparison of Stochastic and Deterministic Results

This case study intends to examine the stochastic modeling of the customers' choice and derive the differences with the deterministic model.

Data on dependency scenarios is considered based on the input energy carriers' prices, as presented in the Appendix, Table III. In addition, as shown in (28)–(33) and Fig. 4, part of the hot water consumption is dependent on the CBDR program and the other part can be supplied by gas or electricity according to customer's choice.

The share of gas and electricity consumption is uncertain because it depends on the consumer's behavior in using electrical and gas-fired water heater and responding to CBDR program. The mentioned uncertainty is considered in the stochastic model. For the sake of a fair comparison, the mean value of the mentioned ratio in the stochastic model is equal to the corresponding amount in the deterministic case.

Figs. 11 and 12 compare the share of CBDR and CS from total dependent demand for both gas and electricity carriers of multienergy demand in stochastic and deterministic situations.

From Fig. 11, most of the consumers tend to have their own choice of the electricity carrier for most of the time, with reduced participation in CBDR in early morning and late night. On the other hand, Fig. 12 shows that the consumers have the tendency to take part in the CBDR program for their gas consumption. This tendency occurs mostly between hours 7–22 where no consumer participates in electric CBDR.

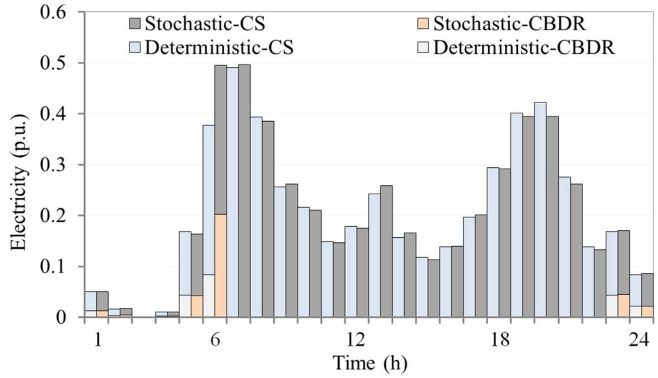

Fig. 11. Contribution of CBDR and CS to the electricity share of dependent demand for deterministic and stochastic models.

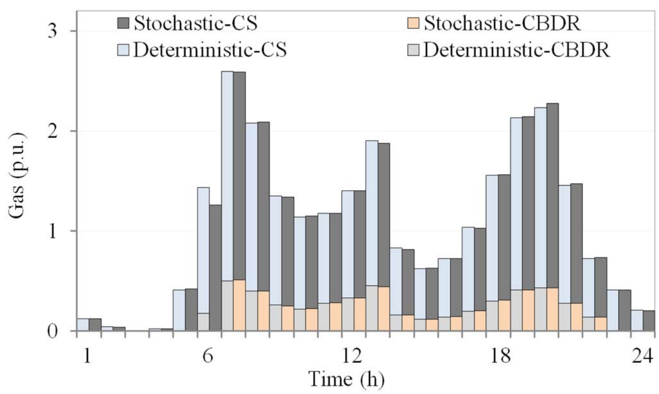

Fig. 12. Contribution of CBDR and CS in gas share of dependent demand for deterministic and stochastic models.

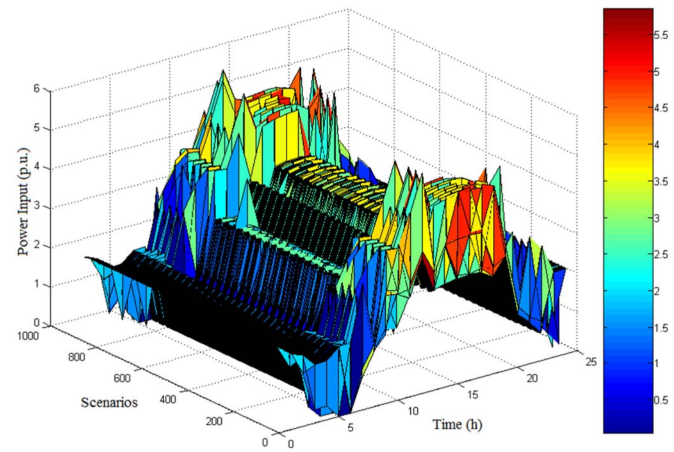

Fig. 13. Electricity input variation for various stochastic scenarios.

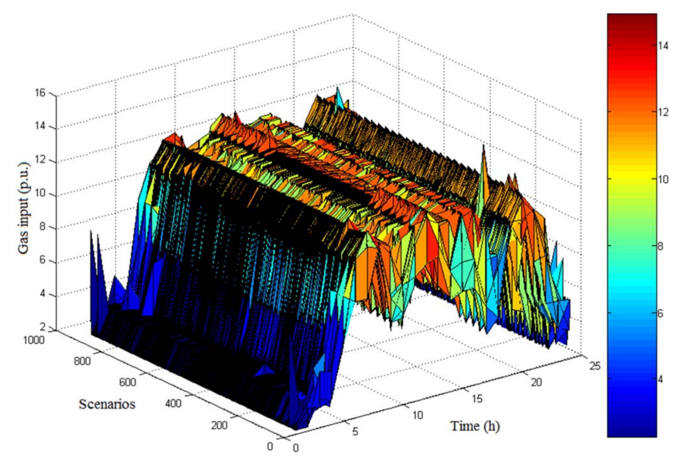

Fig. 14. Gas input variation for various stochastic scenarios.

From Figs. 11 and 12, it can be seen that the results obtained from the deterministic and stochastic models are similar. However, in hour 6 A.M., a significant difference between the results of electricity demand in stochastic and deterministic modeling occurs. The reason is that the assumed system hour 6 A.M. is critical, being the point where the interaction of internal and ED has the highest effect on the operator's decision making. Taking a look at Fig. 6 shows that this hour is the time when the electricity price shows a rise and will have a significant difference from the gas price. Besides, considering Fig. 7, it shows that at the same hour (6 A.M.) the demand for heat has its highest amount. Therefore, the system operator is going to operate the CHP unit in a way to be able to provide the required heat demand. The CHP unit will be producing more electricity; hence, the system operator will decide to reduce the amount of electricity purchased from the upstream network and supply its customers with the electricity produced by the CHP unit. Fig. 9 proves this and indicates that the amount of electricity purchased at 6 A.M. is zero. The situation shows that, in such hours where high link between internal dependencies and EDs may occur, neglecting the stochastic modeling would affect the results on the balance between power and gas inputs seen by the operator.

Figs. 13 and 14 depict the variations of the input electricity and gas for various scenarios of uncertainty for both CBDR and CS. In these figures, for 900 scenarios, the amount of input energy is illustrated. In these figures, the color code is shown in the figure determining the variation between the lowest (dark blue) and highest (dark red) amount of input energy carrier. The figures are plotted using surfaces with black edges. The black areas in these figures show the density of the scenarios' number that occurred with the same trend. In other words, in those areas, there are more scenarios that have equal amount of input carrier in each hour (or with a very small difference) causing the black edges to overlap and form a black area. It also should be noted that the arrangement of the scenarios are in a way that the scenarios are started from the lowest probability of occurrence, then reach the highest probability and after that the probability decreases again. This means that scenarios with numbers 1–100 and 800–900 have the lowest probability.

In Fig. 13, the black area is concentrated for the scenarios number 200–700. This shows that the scenarios that have higher probability of occurrence tend to follow similar trend, while the other scenarios show high distortion in their results. On the other hand, in Fig. 14, the scenarios do not show a dramatic change in the amount, but overlapping edges show that more probable scenarios exist regarding gas input.

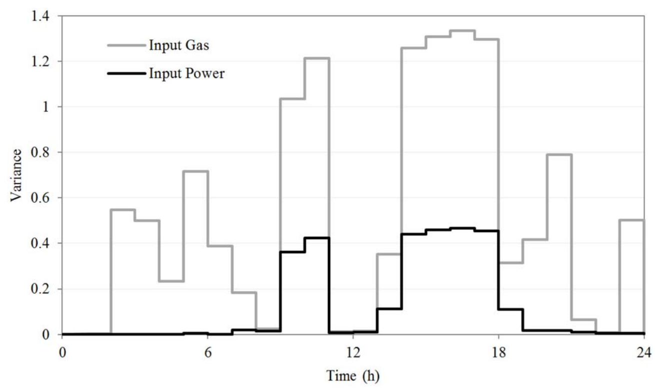

Fig. 15. Variance of input power and gas.

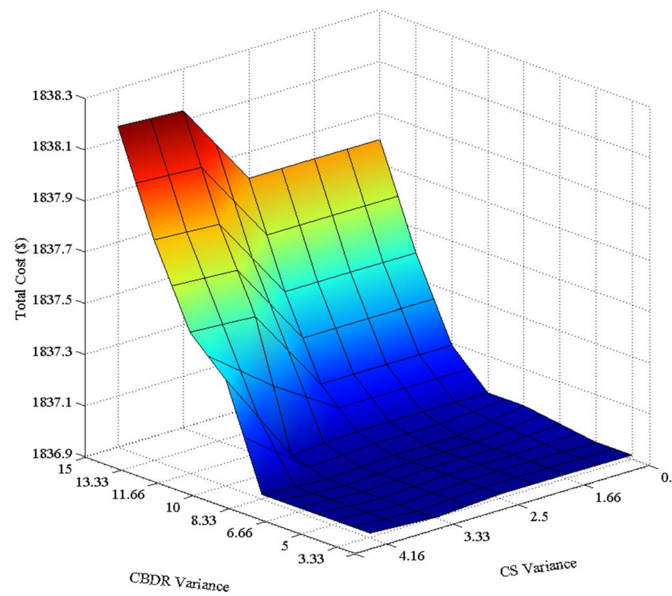

Fig. 16. Variation of total cost versus variation in CBDR and CS variance.

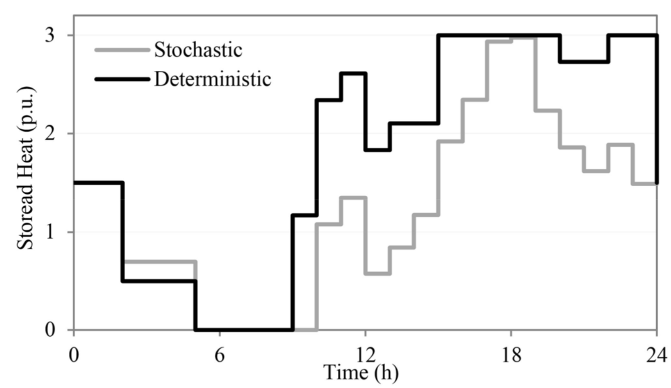

Fig. 17. Stored heat variation in HS for deterministic and stochastic models.

The reason can be found beneath the fact that there are other elements in the multienergy system that help the system operator to damp the effects of harsh uncertain scenarios regarding the gas input energy.

The AB and CHP unit are two elements that help the supply of gas and heat in the system. As a result, in such systems the uncertainty of end users' stochastic behavior can be managed through the internal dependency in the multienergy system.

The results from the scenarios presented in Figs. 13 and 14 are obtained to show the variance of input energy carriers.

Fig. 15 shows that not only the changes in input gas variance are extended to 24 h (while the variance of input power is limited to hours 6–22), but also the amplitude of the variance is higher compared to electricity. The reason is due to various uncertainties that are imposed to the decision making process for the multienergy system's total gas input.

Regarding the gas energy carrier, not only the dependent demand uncertainty should be considered, but also the effects of HS and CHP unit should not be neglected. As the storage has a time-dependent nature, the variance of gas input is extended to various hours.

In addition, the CHP unit's consumption of gas and its conflicts with the independent gas consumption and the dependent demand impose other factors to the decision making problem.

For presenting the mechanics of the stochastic model, Fig. 16 shows the variation of total cost versus the variations in CBDR and CS variance. As it is observed, by increase in the CS variance the total cost increases. On the other hand, the increase in CBDR variance does not impose any significant change in the amount of total cost. The reason is that when the variance of CS is increasing, the uncertainty of customer's choice on different carriers is getting higher. The customer choice referring to CS is not under control by the operator. Conversely, CBDR is also driven by the operator's action in promoting the DR program, and when the CBDR variance is increasing the operator can maintain its cost through scheduling the consumption of the dependent demand. Moreover, it shows that in higher variances of CS, as the CBDR variance increases the total cost will be reduced. This also indicates that the CBDR program will help the operator to reduce its operation costs.

In order to indicate the performance of the stochastic model, the stored heat is presented as one of the decision variables of the operator in Fig. 17.

As it can be seen, the uncertainty of energy carriers' demand in the stochastic model causes the HS to be operated less compared with the deterministic case. The main reason is that a part of stored heat in each hour is wasted as heat loss. Therefore, with higher amount of stored heat more heat loss will be produced in the system, which during the optimization process leads to less utilization of HS from the operator point of view.

VII. Conclusion

For a local multienergy system, this paper has introduced the concepts of dependent demand, referring to a specific service that can be supplied through different energy carriers, internal dependencies (referring to changing the energy source in multienergy flows under the control of the system operator) and EDs (representing changes in the energy source driven by the customer choice of the end user, also due to possible participation in DR programs). A new stochastic model based

TABLE II
DATA OF LOCAL ENERGY NETWORK ELEMENTS

CHP Unit	
Output Energy (Min/Max)	0/5 p.u.
η_e^{CHP}	0.35
η_h^{CHP}	0.45
γ^{CHP} (Min/Max)	1/2
Auxiliary Boiler	
Output Energy (Min/Max)	0/10 p.u.
η_h^{AB}	0.9
Heat Storage	
Stored Energy (Min/Max)	0.5/3 p.u
$\eta_{\alpha,c}^{r}, \eta_{\alpha,d}^{r}$	0.9

TABLE III
DATA ON DEPENDENCY SCENARIOS

Time (hours)		1-5	6-10	11-13	14-22	23-24
CBDR(%)	μ	10	15	20	15	10
	σ	1.66	1.66	1.66	1.66	1.66
Carrier share (%)	μ	69	74	80	74	69
	σ	5	5	5	5	5

on the energy hub approach has been developed to represent the EDs and their uncertainty referring to multienergy system operation. For assessing the efficiency of the developed model, a local energy system was considered and the uncertain behavior of the consumers was modeled in a stochastic framework. The uncertainties include the response of the customers participating in a CBDR program, and the selection of different carriers by the customers not participating in the CBDR program, both affecting the energy carriers share. The numerical results obtained on a case study show how an increased share of participation in the CBDR program can reduce the operational costs. Furthermore, in networks with inefficient DERs it will be more significant to manage part of the demand as DR programs. In addition, the proposed approach enables quantifying to what extent the stochastic dependencies impact on the operating conditions of the system and can vary the schedule of the operator because of the more accurate representation of the relevant variables.

APPENDIX

See Tables II and III.

ACKNOWLEDGMENT

The authors would like to thank the anonymous reviewers for their insightful comments and suggestions, leading to a substantial improvement of this paper.

REFERENCES

[1] K. Alanne and A. Saari, "Distributed energy generation and sustainable development," *Renew. Sustain. Energy Rev.*, vol. 10, no. 6, pp. 539–558, Dec. 2006.

[2] M. F. Akorede, H. Hizam, and E. Pouresmaeil, "Distributed energy resources and benefits to the environment," *Renew. Sustain. Energy Rev.*, vol. 14, no. 2, pp. 724–734, Feb. 2010.

[3] M. A. Pedrasa, E. D. Spooner, and I. F. MacGill, "Improved energy services provision through the intelligent control of distributed energy resources," in *Proc. IEEE PowerTech,* Bucharest, Romania, 2009, pp. 1–8.

[4] P. Stroehle, C. Flath, and C. Weinhardt. (2012). *An Online Mechanism for Incorporating Demand Side Flexibility into the Smart Grid*. [Online]. Available: http://dx.doi.org/10.2139/SSRN.2191530

[5] G. Chicco and P. Mancarella, "Distributed multi-generation: A comprehensive view," *Renew. Sustain. Energy Rev.*, vol. 13, no. 3, pp. 535–551, Apr. 2009.

[6] M. Geidl *et al.*, "Energy hubs for the future," *IEEE Power Energy Mag.*, vol. 5, no. 1, pp. 24–30, Jan./Feb. 2007.

[7] M. Moeini-Aghtaei, A. Abbaspour, M. Fotuhi-Firouzabadi, and E. Hajipour, "A decomposed solution to multiple-energy carriers optimal power flow," *IEEE Trans. Power Syst.*, vol. 29, no. 2, pp. 707–716, Mar. 2014.

[8] M. Geidl and G. Andersson, "Operational and topological optimization of multi-carrier energy systems," in *Proc. Int. Conf. Future Power Syst.*, Amsterdam, The Netherlands, Nov. 2005, pp. 6–18.

[9] M. Arnold and G. Andersson, "Decomposed electricity and natural gas optimal power flow," in *Proc. 16th Power Syst. Comput. Conf. (PSCC)*, Glasgow, Scotland, 2008, pp. 1–7.

[10] M. Geidl, "Integrated modeling and optimization of multi-carrier energy systems," Ph.D. dissertation, Dept. Inf. Technol. Elect. Eng., ETH Univ., Zürich, Switzerland, 2007.

[11] A. Hajimiragha, C. Cañizares, M. Fowler, M. Geidl, and G. Andersson, "Optimal energy flow of integrated energy systems with hydrogen economy considerations," in *Proc. IREP Symp. Bulk Power Syst. Dyn. Control*, Charleston, SC, USA, Aug. 2007, pp. 1–11.

[12] M. Shulze and P. C. Del Granado, "Optimization modeling in energy storage applied to a multi-carrier system," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Minneapolis, MN, USA, Jul. 2010, pp. 1–7.

[13] M. La Scala, A. Vaccaro, and A. F. Zobaa, "A goal programming methodology for multi objective optimization of distributed energy hubs operation," *Appl. Thermal Eng.*, vol. 71, no. 2, pp. 658–666, 2014.

[14] M. Geidl and G. Andersson, "Optimal coupling of energy infrastructures," in *Proc. IEEE Power Tech*, Lausanne, Switzerland, Jul. 2007, pp. 1398–1403.

[15] M. Arnold and G. Andersson, "Model predictive control of energy storage including uncertain forecasts," in *Proc. Power Syst. Comput. Conf. (PSCC)*, Stockholm, Sweden, 2011, pp. 1–7.

[16] F. Adamek, M. Arnold, and G. Andersson, "On decisive storage parameters for minimizing energy supply costs in multicarrier energy systems," *IEEE Trans. Sustain. Energy*, vol. 5, no. 1, pp. 102–109, Jan. 2014.

[17] A. Parisio, C. Del Vecchio, and A. Vaccaro, "A robust optimization approach to energy hub management," *Elect. Power Energy Syst.*, vol. 42, no. 1, pp. 98–104, Nov. 2012.

[18] T. Capuder, and P. Mancarella, "Techno-economic and environmental modelling and optimization of flexible distributed multi-generation options," *Energy*, vol. 71, pp. 516–533, Jul. 2014.

[19] M. C. Bozchalui, S. A. Hashmi, H. Hassen, C. A. Cañizares, and K. Bhattacharya, "Optimal operation of residential energy hubs in smart grids," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1755–1766, Dec. 2012.

[20] M. Geidl, P. Favre-Perrod, B. Klöckl, and G. Koeppel, "A greenfield approach for future power systems," in *Proc. Cigre Gen. Session 41*, Paris, France, 2006, pp. 1–8.

[21] M. S. Nazar and M. R. Haghifam, "Multiobjective electric distribution system expansion planning using hybrid energy hub concept," *Elect. Power Syst. Res.*, vol. 79, pp. 899–911, Jun. 2009.

[22] F. Kienzle and G. Andersson, "A greenfield approach to the future supply of multiple energy carriers," in *Proc. IEEE Power Energy Soc. Gen. Meeting (PES)*, Calgary, AB, Canada, Jul. 2009, pp. 1–8.

[23] F. Kienzle, E. Trutnevyte, and G. Andersson, "Comprehensive performance and incertitude analysis of multi-energy portfolios," in *Proc. IEEE PowerTech*, Bucharest, Romania, Jul. 2009, pp. 1–6.

[24] F. Kienzle and G. Andersson, "Efficient multi-energy generation portfolios for the future," in *Proc. 4th Annu. Carnegie Mellon Conf. Elect. Ind.*, Pittsburgh, PA, USA, 2008, pp. 1–18.

[25] F. Kienzle, P. Ahčin, and G. Andersson, "Valuing investments in multi-energy conversion, storage, and demand-side management systems under uncertainty," *IEEE Trans. Sustain. Energy,* vol. 2, no. 2, pp. 194–202, Apr. 2011.

[26] G. Koeppel, "Reliability considerations of future energy systems: Multi-carrier systems and the effect of energy storage," Ph.D. dissertation, Dept. Inf. Technol. Elect. Eng., ETH Univ., Zürich, Switzerland, 2007.

[27] M. R. Haghifam and M. Manbachi, "Reliability and availability modeling of combined heat and power (CHP) systems," *Int. J. Elect. Power Energy Syst.*, vol. 33, no. 3, pp. 385–393, Mar. 2011.

[28] M. Almassalkhi and I. Hiskens, "Cascade mitigation in energy hub networks," in *Proc. 50th IEEE Conf. Decis. Control Eur. Control Conf.*, Orlando, FL, USA, Dec. 2011, pp. 2181–2188.

[29] M. Almassalkhi and I. Hiskens, "Impact of energy storage on cascade mitigation in multi-energy systems," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, San Diego, CA, USA, Jul. 2012, pp. 1–8.

[30] A. Shahmohammadi, M. Moradi-Dalvand, H. Ghasemi, and S. Ghazizadeh, "Optimal design of multi-carrier energy systems considering reliability constraints," *IEEE Trans. Power Del.*, vol. 30, no. 2, pp. 878–886, Apr. 2015.

[31] M. D. Galus and G. Andersson, "Power system considerations of plug-in hybrid electric vehicles based on a multi energy carrier model," in *Proc. IEEE Power Energy Soc. Gen. Meeting (PES)*, Calgary, AB, Canada, Jul. 2009, pp. 1–8.

[32] M. Moeini-Aghataie, P. Dehghanian, M. Fotuhi-Firouzabad, and A. Abbaspour, "Multiagent genetic algorithm: An online probabilistic view on economic dispatch of energy hubs constrained by wind availability," *IEEE Trans. Sustain. Energy*, vol. 5, no. 2, pp. 699–708, Apr. 2014.

[33] S. Pazouki, M. R. Haghifam, and A. Moser, "Uncertainty modeling in optimal operation of energy hub in presence of wind, storage and demand response," *Elect. Power Energy Syst.*, vol. 61, pp. 335–345, Oct. 2014.

[34] M. D. Galus, S. Koch, and G. Andersson, "Provision of load frequency control by PHEVs, controllable loads, and a cogeneration unit," *IEEE Trans. Ind. Electron.*, vol. 58, no. 10, pp. 4568–4582, Oct. 2011.

[35] M. D. Galus and G. Andersson, "Integration of plug-in hybrid electric vehicles into energy networks," in *Proc. IEEE PowerTech*, Bucharest, Romania, Jul. 2009, pp. 1–8.

[36] G. Chicco and P. Mancarella, "Matrix modeling of small-scale trigeneration systems and application to operational optimization," *Energy*, vol. 34, no. 3, pp. 261–273, Mar. 2009.

[37] P. Mancarella, "MES (multi-energy systems): An overview of concepts and evaluation models," *Energy*, vol. 65, pp. 1–17, Feb. 2014.

[38] D. Manz *et al.*, "The grid of the future: Ten trends that will shape the grid over the next decade," *IEEE Power Energy Mag.*, vol. 12, no. 3, pp. 26–36, May/Jun. 2014.

[39] P. T. Baboli, M. Eghbal, M. P. Moghaddam, and H. Aalami, "Customer behavior based demand response model," in *Proc. IEEE Power Energy Soc. Gen. Meeting (PES)*, San Diego, CA, USA, Jul. 2012, pp. 1–7.

[40] P. Mancarella and G. Chicco, "Real-time demand response from energy shifting in distributed multi-generation," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 1928–1938, Dec. 2013.

[41] E. Koch and M. A. Piette, "Architecture concepts and technical issues for an open, interoperable automated demand response infrastructure," in *Proc. Grid Interop Forum*, Albuquerque, NM, USA, Nov. 2007, pp. 1–7.

[42] Q. B. Dam, S. Mohagheghi, and J. Stoupis, "Intelligent demand response scheme for customer side load management," in *Proc. Energy 2030 Conf.*, Atlanta, GA, USA, Nov. 2008, pp. 1–7.

[43] M. Houwing, R. R. Negenborn, and B. De Schutter, "Demand response with micro-CHP systems," *Proc. IEEE*, vol. 99, no. 1, pp. 200–213, Jan. 2011.

[44] T. Krause, G. Andersson, K. Fröhlich, and A. Vaccaro, "Multiple-energy carriers: Modeling of production, delivery, and consumption," *Proc. IEEE*, vol. 99, no. 1, pp. 15–27, Jan. 2011.

[45] T. K. Wijaya, T. G. Papioannou, X. Liu, and K. Aberer, "Effective consumption scheduling for demand-side management in the smart grid using non-uniform participation rate," in *Proc. Sustain. Internet ICT Sustain. (SustainIT)*, Palermo, Italy, Oct. 2013, pp. 1–8.

[46] T. K. Wijaya, M. Vasirani, and K. Aberer, "When bias matters: An economic assessment of demand response baselines for residential customers," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1755–1763, Jul. 2014.

[47] J. M. Morales, A. J. Conejo, and J. Pérez-Ruiz, "Short-term trading for a wind power producer," *IEEE Trans. Power Syst.*, vol. 25, no. 1, pp. 554–564, Feb. 2010.

[48] A. Kusiak, H. Y. Zheng, and Z. Song, "Power optimization of wind turbines with data mining and evolutionary computation," *Renew. Energy*, vol. 35, no. 3, pp. 695–702, 2010.

[49] A. J. Conejo, M. Carrión, and J. M. Morales, "Decision making under uncertainty in electricity markets," in *Uncertainty Characterization via Scenarios*. New York, NY, USA, Springer, 2010.

[50] J. Dupacova, N. Growe-Kuska, and W. Romisch, "Scenario reduction in stochastic programming: An approach using probability metrics," *Math. Program. A,* vol. 95, no. 3, pp. 493–511, 2003.

[51] H. Heitsch and W. Romisch, "Scenario reduction algorithms in stochastic programming," *Comput. Optim. Appl.*, vol. 24, nos. 2–3, pp. 187–206, 2003.

[52] N. Amjady, J. Aghaei, and H. A. Shayanfar, "Stochastic multiobjective market clearing of joint energy and reserves auctions ensuring power system security," *IEEE Trans. Power Syst.*, vol. 24, no. 4, pp. 1841–1854, Nov. 2009.

[53] *Buildings Energy Data Book*, U.S. Dept. Energy, Washington, DC, USA, 2010. [Online]. Available: http://buildingsdatabook.eren.doe.gov/default.aspx

[54] K. Latorre, J. M. Latorre, L. Olmos, and A. Ramos, "Demand response and its sensitivity to participation rates and elasticities," in *Proc. 8th Int. Conf. Eur. Energy Market (EEM)*, Zagreb, Croatia, May 2011, pp. 711–716.

Nilufar Neyestani (S'09) received the M.Sc. degree in electrical engineering from the Iran University of Science and Technology, Tehran, Iran, in 2010. She is currently pursuing the Ph.D. degree with the Laboratory of Sustainable Energy Systems, University of Beira Interior, Covilha, Portugal, under the guidance of Prof. J. P. S. Catalão.

Her current research interests include electric vehicles, smart grids, power system planning, power system optimization, multienergy systems, and energy hub.

Maziar Yazdani-Damavandi (S'08) received the M.Sc. degree in electrical engineering from Tarbiat Modares University, Tehran, Iran, in 2010, where he is currently pursuing the Ph.D. degree with the Energy Management Laboratory.

He is a Researcher on the SiNGULAR Project with the University of Beira Interior, Covilha, Portugal. His current research interests include optimization models in power system studies and multienergy system modeling.

Miadreza Shafie-khah (S'08–M'13) received the M.Sc. and Ph.D. degrees in electrical engineering from Tarbiat Modares University, Tehran, Iran, in 2008 and 2012, respectively. He is currently pursuing the Post-Doctoral degree with the Laboratory of Sustainable Energy Systems, University of Beira Interior, Covilha, Portugal, under the guidance of Prof. J. P. S. Catalão.

His current research interests include power market simulation, market power monitoring, power system optimization, operation of electricity markets, price forecasting, and smart grids.

Gianfranco Chicco (M'98–SM'08) received the Ph.D. degree in electrotechnics engineering from Politecnico di Torino (PdT), Torino, Italy, in 1992.

He is currently a Professor of Electrical Energy Systems with the Energy Department, PdT. His current research interests include power system and distribution system analysis, energy efficiency, multigeneration, load management, artificial intelligence applications, and power quality.

Prof. Chicco is a Member of the Italian Association of Electrical, Electronic, and Telecommunications Engineers.

João P. S. Catalão (M'04–SM'12) received the M.Sc. degree from the Instituto Superior Técnico, Lisbon, Portugal, in 2003, and the Ph.D. degree and Habilitation for Full Professor ("Agregação") from the University of Beira Interior (UBI), Covilha, Portugal, in 2007 and 2013, respectively.

He is a currently a Professor and the Director with the Sustainable Energy Systems Laboratory, UBI, and a Researcher with INESC-ID, Lisbon. He is the Primary Coordinator of the EU-funded FP7 Project Smart and Sustainable Insular Electricity Grids Under Large-Scale Renewable Integration. His current research interests include power system operations and planning, hydro and thermal scheduling, wind and price forecasting, distributed renewable generation, demand response, and smart grids. He has authored or co-authored over 350 publications, including 105 journal papers, 220 conference proceedings papers, and 20 book chapters, with an H-index of 23 (Google Scholar), and he has supervised over 25 Post-Doctorates, Ph.D., and M.Sc. students. He has edited the book *Electric Power Systems: Advanced Forecasting Techniques and Optimal Generation Scheduling* (CRC Press, 2012). He is currently editing another book entitled *Smart and Sustainable Power Systems: Operations, Planning and Economics of Insular Electricity Grids* (CRC Press, 2015).

Prof. Catalão was a recipient of the 2011 Scientific Merit Award UBI-FE/Santander Universities and the 2012 Scientific Award UTL/Santander Totta. He is an Editor of the IEEE TRANSACTIONS ON SMART GRID and the IEEE TRANSACTIONS ON SUSTAINABLE ENERGY, and an Associate Editor of *IET Renewable Power Generation*. He was the Guest Editor-in-Chief for the Special Section on Real-Time Demand Response of the IEEE TRANSACTIONS ON SMART GRID in 2012. He is currently the Guest Editor-in-Chief for the Special Section on Reserve and Flexibility for Handling Variability and Uncertainty of Renewable Generation of the IEEE TRANSACTIONS ON SUSTAINABLE ENERGY.