Stochastic Analysis and Reliability-Cost Optimization of Distributed Generators and Air Source Heat Pumps

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***Abstract*—This paper presents a framework for stochastic analysis, simulation and optimisation of electric power grids combined with heat district networks. In this framework, distributed energy sources can be integrated within the grids and their performance is modelled. The effect of uncertain weather-operational conditions on the system cost and reliability is considered. A Monte Carlo Optimal Power Flow simulator is employed and statistical indicators of the system cost and reliability are obtained. Reliability and cost expectations are used to compare 4 different investments on heat pumps and electric power generators to be installed on a real-world grid. Generators' sizes and positions are analysed to reveal the sensitivity of the cost and reliability of the grid and an optimal investment problem is tackled by using a multi-objective genetic algorithm.**

***Keyworkds*- Renewable Power; Interconnected Grids Reliability; Heat Pumps; Sensitivity; Stochastic Optimisation;**

I. Introduction

The present view on Smart Grid projects (e.g. [1]) generally rates the power grid as the most prominent infrastructure whilst different systems (e.g. transportation and heat district networks) received a relatively limited consideration. In the last years, however, several researchers pointed out the benefits of combining analysis of power grids to different networked systems which are inevitably linked. For instance, integrated analysis of the so-called multi-energy-systems (i.e. systems for which electricity, heating, cooling, fuels, transport optimally interact with each other [2]- [3]) can help better understand collective behaviours and interactions between interconnected grids.

Investments in renewable energy sources (RES) and energy-efficient buildings can play an important role in designing more reliable and sustainable future grids. Distributed Generators (DGs) and RES, if smartly integrated within power grids, and can reduce electric energy losses, minimise carbon dioxide emission and improve grid reliability [4]. However, the high uncertainty associated with their power outputs generally discourages investments on high energy penetration levels [5]- [6]. The overall buildings energy consumption shares a large amount of total energy demand of developed countries (up to 40%) [7]. Improve energy efficiency of building and heat power supply reliability is necessary and, for this purpose, buildings envelopes can be enhanced and efficient heating and cooling systems installed (e.g. exploiting renewable air and ground energy [8]- [9]). If energy-efficient technologies are employed, air source heat pumps are some of the most viable options on the market.

Air source Heat Pumps (HPs) transfer heat by exploiting a refrigeration cycle and often result economically convenient due to high coefficients of performance (i.e. efficiency). One of the major downsides is that their operative states are strongly affected by uncertain, variable ambient air temperate and, thus, some sort of heating backup system is normally required to guarantee a reliable heating supply [9]. An increasing number of research papers discussed the effects of combining heat pumps with renewable distributed electric generators [10]. However, to the author's knowledge, just a few works embedded distributed air source heat pumps model within stochastic frameworks for uncertainty quantification. For instance, Cesena, Capuder and Mancarella [11] proposed an optimisation framework for distributed multi-energy-systems allocating combined heat power devices and considering long-term uncertainty.

This paper presents a computational framework for stochastic simulation and optimisation of distributed generators within interconnected heat and electric power grids. Electric and heat power generators can be allocated within the nodes of the grid. The renewable power outputs are affected by variable weather conditions and relevant sources of uncertainty are considered within the stochastic model (e.g. electric and thermal load variability, wind speed variability, etc.). Linkage functions are specifically designed to couple the heating system to the electrical grid and a Monte Carlo Optimal-Power-Flow (MC-OPF) simulator is used to assess the system reliability and cost. A variance-based sensitivity analysis method is adopted to reveal the effect of different generators type, size and location on the system cost and reliability. To conclude, a multi-objective optimisation method is adopted to find a set of good investments strategies, i.e. the optimal DGs expansion plan which minimises both the system cost and unreliability index. The framework is flexible and can account for the unavailability of specific components (e.g. unplanned maintenance for Heat pumps or WT) although are here neglected for simplicity. In a future extension of the work, random components failures will be considered.

II. Stochastic Weather and Components Modelling

The structure of a power grid can be mathematically represented by a graph $\mathcal{G}_{el}(\mathcal{N}_{el}, \mathcal{E}_{el})$, such that i are nodes within the set of electric grid nodes $\mathcal{N}_{el}$ and $l = (i, j)$ are electric cables (between nodes i and j) within the lines set $\mathcal{E}_{el}$. Similarly, the structure of a district heating network can be represented by a graph $\mathcal{G}_{th}(\mathcal{N}_{th}, \mathcal{E}_{th})$ where $\mathcal{E}_{th}$ is the pipes set.

A. Weather Model and Power Loads

The weather model assumes the wind speed (v), the solar irradiance (s) and the external air temperature (T_{ext}) to be random variables distributed as a Rayleigh, Beta and Normal PDF, respectively [4]. The parameters of the distributions (σ_v, a, b, $\mu_{T_{ext}}$ and $\sigma_{T_{ext}}$) are estimated using historical data for the geographical location in exam. For simplicity, the weather condition is assumed uniform over $\mathcal{G}_{el}$ and $\mathcal{G}_{th}$.
The electric and thermal power load ($L_{th,i}(t)$ and $L_{th,i}(t)$) at node i and time t are characterised by normal probability distributions [4]; the parameters of the distributions $\sigma_{el,i}(t)$, $\mu_{el,i}(t)$, $\sigma_{th,i}(t)$ and $\mu_{th,i}(t)$ estimated using historical data.

B. Electric Power Distributed Generators

Four types of electric power DGs are considered: Wind Turbines (WT), Photovoltaic panels (PV), Storage systems (ST) and Electric Vehicles (EV). A probabilistic model for DGs is adopted and for its complete description, the reader is reminded [4]- [12].

1) Wind Turbines and Photovoltaic Panels: The power produced by a wind turbine, $P_w(v)$, depends on the (random) wind speed v, the cut-in wind speed v_{ci} in [m/s], the rated wind speed v_r in [m/s], the cut-out wind speed v_{co} in [m/s] and the rated power output for the turbine P_w^{ra} in [kW] [4].
The power output from PV is computed as $P_{pv}(s, T_{ext}) = n_{cells} \cdot FF \cdot V \cdot I$, where n_{cells} is its number of cells, FF is the filling factor and the current I and the voltage V are related to the sun radiation s, the external air temperature T_{ext} [12].

2) Storage Systems and Electric Vehicles: Storage systems and, similarly, electric vehicles can inject or withdraw electric power from the network. Three EVs operating states (op) are considered: the vehicle to grid (V2G), the grid to vehicle (G2V) and the disconnected, discrete probability mass is associated to the operative states $f(t, op)$. The power injected or demanded by EVs, $P_{ev}(op)$, is equal to plus or minus the rated power P_{EV}^{ra} [kW] if the vehicle are in the discharging or charging states, respectively. If the randomly sampled operative state result disconnected, $P_{ev}(op)$ is set to 0. The model for storage systems is analogous [4] but, for simplicity, only discharge operative states are considered.

C. Heat Pumps

The thermal power output P_{HP} of an air-to-water mono compressor On-Off HP depends on the external air temperature as follows [9]:

$$P_{HP}(T_{ext}) = a_1(T_w) \cdot T_{ext} + b_1(T_w) \cdot T_{ext}^2 + c_1(T_w)$$

Similarly, the HP's coefficient of performance at full load depends on T_{ext} as follows [9]:

$$COP_{DC}(T_{ext}) = a_2(T_w) \cdot T_{ext} + b_2(T_w) \cdot T_{ext}^2 + c_2(T_w)$$

where T_w is the hot water temperature provided to the thermal load and the regression coefficients $a_1, a_2, b_1, b_2, c_1, c_2$. In the proposed model, T_w is assumed to be 35 $°C$ and constant, this is a realistic assumption when the HP is coupled to a radiant floor heating loop during the heating season [9]- [13]. The HP temperature operating limit (TOL) depends on the specific heat pump. For the On-Off HP analysed in this work TOL is equal to -10 $°C$ and the heat limit external temperature is assumed to be +16 $°C$. Thus, if $T_{ext} > +16°C$ or $T_{ext} < -10°C$, P_{HP} is set to 0.

D. Heat and Electric Power Coupling

The thermal power output P_{HP} of an heat pump is related to the electrical power demanded by the pump $L_{HP,el}$ trough the coefficient of performance COP_{PL} at partial loads, $L_{HP,el} = \frac{P_{HP}}{COP_{PL}}$. The COP_{PL} takes into account the losses linked to the on-off conditions when the pump is operated at partial regime and can be obtained by weighting the COP_{DC} for a function of the thermal load, the HP power output and a degradation coefficient (see [9] for further details).
In this model when $P_{HP,i} < L_{th,i}$, the residual heat demand in the node i is fulfilled by an back-up heating system. For simplicity, only electric back-up systems are considered. If the heat power demand exceeds the production, the electric power required by the back-up system is $L_{BU,el}(t) = L_{th}(t) - P_{HP}(t)$, where the node index i has been dropped for ease of notation. The aggregated electric power demand at each node is simply obtained as $L_{el}(t) = P_{d,el}(t) + L_{HT,el}(t) + L_{BU,el}(t)$, where $P_{d,el}(t)$ is the random component of the electric power demanded by node i at time t.

III. Monte Carlo Optimal Power Flow and Reliability Index

In this work, a Monte Carlo Optimal-Power-Flow [4] is employed to evaluate the effect of uncertainty over the system. The MC-OPF procedure is summarised by the following 5 steps:

1. **Initialisation:** Provide DGs size, type and location. Input number of Monte Carlo runs (N_{MC}) and parameters of the stochastic model.
2. **Sampling:** Random sample the uncertain weather variables (s, v, T_{ext}), the time of the day (t) and the grids components operative states ($op(t)$, E_{st}, $L_{th}(t)$, $L_{el}(t)$) from the stochastic model.
3. **Loads/production:** The weather conditions are used to compute the available power from renewable generators (see Section II-B and II-C). The coupling equations are solved and electric load increased by the electric power demanded by HPs and back-up systems.
4. **Grid Analysis:** The electric load and the DGs power outputs are forwarded to an optimal power flow (OPF) solver in Eq.1. Outputs are the minimum operative cost for the grid $C_{O,i}^{min}$ and an indicator of the system reliability and the Energy-not-Supplied (ENS) computed as $ENS = \sum_{t=1}^{T_h} \sum_{j\in\mathcal{N}_{el}} L_{cut,j,t} \cdot T_h$, where $L_{cut,j,t}$ is the load curtailed at node j at time t and T_h is the simulation time.
5. **Collect Results:** Steps 2, 3 and 4 are repeated N_{MC} times. The probability density function of the ENS and C_{glb} are obtained and the expectations computed as $\mathbb{E}[ENS] = \sum_{i=1}^{N_{MC}} ENS_i/N_{MC}$ and $\mathbb{E}[C_{glb}] = \sum_{i=1}^{N_{MC}} (C_{O,i}^{min} + C_{inv} - C_{inc,i})/N_{MC}$. C_{inv} is the cost of the investment in DGs, $C_{inc,i}$ is a gain due to the incentives available for producing power with renewable sources.

The cost C_{inv} is computed as $C_{inv} = \sum_J (N_J \cdot C_{inv,J}/T_{inv,J})$ and depends only on the initial investment cost on distributed gnerators of type J (i.e. the number N_J times cost per module), prorated hourly over the lifetime $T_{inv,J}$. The gain due to available incentives is computed as $\sum_J Inc_J \cdot P_{g,J}$ and depends on the random amount of renewable power produced within the scenario i. Inc_J is the available incentives for producing a unit of power with J and is assumed here to be 2.61 [p/kWh] for renewable air source heat power [14] and 2.4 [p/kWh] plus the price of the electricity (computed as in [4]) which is saved thanks to the renewable production.

The optimal power flow solves the economic dispatch problem for the grid, i.e. it schedules the power produced by the generators P_g so that the operational cost is minimised . In this optimal power flow formulation loads can be curtailed [4], this is done if operational or physical constraints (e.g. line thermal limits, generators capacity, etc.) cannot be fulfilled otherwise. Mathematically, the minimization problem is defined as follows [15]:

$$C_{O,i}^{min} = \min_{P_g, L_{cut}} \quad \sum_{g=1}^{N_g} C_g \cdot P_g + \sum_{i=1}^{N_l} C_{cut} \cdot L_{cut,i} \qquad (1)$$

where $C_{O,i}^{min}$ is the minimum total operative cost for the power grid, N_g is the total number of electric power generators allocated within the electric grid (including DGs), and C_g and C_{cut} are the cost per-unit of power for the generators and the load curtailed, respectively.

IV. Multi Objective Optimisation: Optimal Power Sources Allocation

The goal of the optimisation analysis is to identify an optimal investment plan on distributed generators (i.e. optimal HPs, WTs, PVs, STs and EVs sizes and positions) which minimises both the $E[ENS]$ and $E[C_{glb}]$. The Non-Dominated Sorted Genetic Algorithm version two (NSGA-II) is the solver used due to the highly non-linear behaviour of the system and not treatable analytical solution [4]. The optimisation procedure can be summarised as follows: First, the number of generations N_{gen}, the population size N_{pop}, the number of MC-OPF runs are selected. A population of chromosome **Chrom** $= [\mathbf{PV}, \mathbf{ST}, \mathbf{WT}, \mathbf{EV}, \mathbf{HP}]$ is generated where, for instance, **PV** is an $[1 \times |\mathcal{N}_{el}|]$ vector and the i^{th} element contains the number of PVs allocated within the i^{th} electric node. Each chromosome **Chrom** is forwarded to the MC-OPF (see Section III) and its $\mathbb{E}[ENS]$ and $\mathbb{E}[C_{glb}]$ are estimated. Then the evolutionary procedure is performed, which includes sorting and ranking the chromosomes based on non-domination and crowding distance criteria an use binary crossover and polynomial mutation operations to create new generations of chromosomes. The evolutionary routine is repeated until the predefined number of generation N_{gen} is reached.

V. Case Study: The Barry Island Network

The Barry island combined heat-electric system [2] is selected to test the framework. The layout for the multi-energy system is presented in Fig.1. The district heating network is composed of 32 nodes of which 20 are heat demand nodes (i.e. aggregation of buildings' heat loads). Differently from Fig.1 and accordingly to [2], an additional heat power demand is considered in node 7 and connected to the first electric busbar (i in Fig.1). The power grid is composed of 8 bus bars, 3 main generator sources in nodes 2, 8 and 7 and 5 electric loads, lumped from the heat network as displayed in Fig.1. The 7 electric cables current rating is 400 [A] and resistances and reactances are R =0.164 and X =0.08 [Ω/km], respectively. For simplicity, the pipes of the district heating network are neglected and only its nodes are considered in this analysis. For further details on the system, the reader is referred to [2]. The mean values and standard deviations of the thermal and electric loads are assumed to be a percentage of the reference loads which are displayed in Fig.1, adapted from [2]. Examples of the thermal and electric power load realisation over 10 days simulation are presented in the upper and lower panel in Fig.2, respectively. The parameters of the weather stochastic model, DGs and heat pumps are reported in Table I.

A. Results of the Stochastic Analysis

The uncertainty in the system reliability index and cost is quantified using the Monte Carlo algorithm presented in

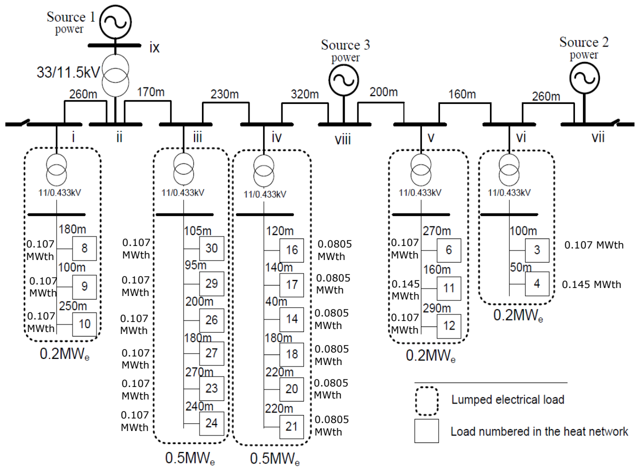

Fig. 1. The Barry island power grid and heat network (modified from [2]). In the figure are displayed links lengths, main electric generators positions and the reference magnitude for electric and thermal loads at each node.

TABLE I
THE DGS PARAMETERS AND THE STOCHASTIC WEATHER MODEL.

Heat and Electric Power DGs' parameters [4]- [9]- [12]			
WT	ST & EV	PV	On-Off HP
$v_{co} = 23.8$	$E_S = 0.042$	$V_{oc} = 55.5$	$a_1 = 0.839$
$v_{ci} = 3.8$	$P_{st}^{ra} = 0.275$	$I_{MPP} = 1.38$	$a_2 = 0.0874$
$v_r = 9.5$	$C_{inv} = 6.76e3$	$N_ot = 43$	$b_1 = 0.011$
$P_w^{ra} = 50$		$I_{sc} = 1.8$	$b_2 =$ 12e-4
$C_{inv} = 1.13e5$	$P_{ev}^{ra} = 6.3$	$V_{MPP} = 38$	$c_1 = 0.877$
	$C_{inv} = 1.65e4$	$k_i = 1.40$	$c_2 = 0.103$
		$k_v = 194$	$T_w = 35$
		$k_v = 194$	$C_{inv} =$ 1e4
		$C_{inv} = 2.4e3$	

Parameters of the Stochastic Weather Model		
Wind	Sun	Temperature
$\sigma_v = 7.96$	$a = 0.26$	$\mu_{T_{ext}} = 6$
	$b = 0.73$	$\sigma_{T_{ext}} = 3$

Section III and 4 cases have been analysed. In the first case (C-1), the original network is tested (neither heat nor electric power generators have been allocated). For the second investment case (C-2), the electric grid invests on distributed electric power generators (5 PVs, 5 STs, 1 WT and 1 EV in each node) but not on heat power generators. Case 3 (C-3) accounts for an investment on both electric and heat power generators (equivalent to C-2 but also 1 heat pump is allocated within each node of the heat network). For case 4 (C-4) only heat pumps have been installed. The 4 different cases are summarised using a simple vector notation as follows (see Section IV):

$$\text{C-1} \quad [\mathbf{PV}, \mathbf{ST}, \mathbf{WT}, \mathbf{EV}, \mathbf{HP}] = [\mathbf{0}, \mathbf{0}, \mathbf{0}, \mathbf{0}, \mathbf{0}]$$
$$\text{C-2} \quad [\mathbf{PV}, \mathbf{ST}, \mathbf{WT}, \mathbf{EV}, \mathbf{HP}] = [\mathbf{5}, \mathbf{5}, \mathbf{1}, \mathbf{1}, \mathbf{0}]$$
$$\text{C-3} \quad [\mathbf{PV}, \mathbf{ST}, \mathbf{WT}, \mathbf{EV}, \mathbf{HP}] = [\mathbf{5}, \mathbf{5}, \mathbf{1}, \mathbf{1}, \mathbf{1}]$$
$$\text{C-4} \quad [\mathbf{PV}, \mathbf{ST}, \mathbf{WT}, \mathbf{EV}, \mathbf{HP}] = [\mathbf{0}, \mathbf{0}, \mathbf{0}, \mathbf{0}, \mathbf{1}]$$

The MC-OPF run number was set to 3000 and the results of each run are the probability distribution functions of the ENS

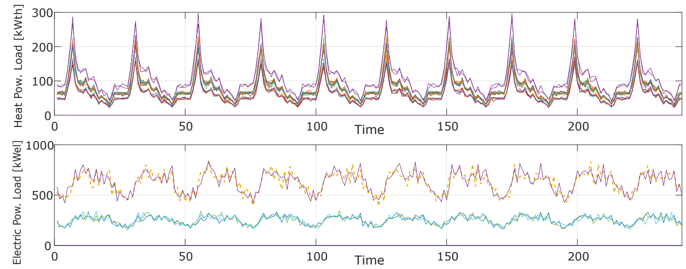

Fig. 2. An examples of random realisation of thermal power and nodal electric power demanded at each node over a simulation time of 240 hours.

and C_{glb}. The results for the expectations, the coefficients of variations (C_V) and the 95th percentiles (p_{95}) are reported in TableII. It can be observed that C-1 produces the lower $\mathbb{E}[C_{glb}]$ and lower grids reliability (i.e. higher $\mathbb{E}[ENS]$) whilst the case with a significant investment (C-3) resulted in the higher reliability but also higher costs. On the other hand, C-2 and C-4 resulted in a compromise solution, i.e. they improved less the system reliability but for a moderate cost. The results pointed out that a combined investment on HP and electric power generators can result in a positive enhancement of the system reliability. Investing on DGs can lead to higher expected reliability, however, the C_V increases when renewable sources are allocated in the grids. This indicates an higher variability and possibly higher risk of hazardous, extreme, low probability scenarios if renewable energy sources are adopted.

TABLE II
THE RESULTS FOR THE 4 INVESTMENT CASES ON DGS

Case	C-1	C-2	C-3	C-4
$\mathbb{E}[ENS]$	1110.4	793.7	498	723.9
$C_V[ENS]$	0.59	0.85	1.18	0.87
$p_{95}[ENS]$	2286	2178	1617	1779
$\mathbb{E}[C_{glb}]$	179.5	203.2	209.7	203.8
$C_V[C_{glb}]$	0.45	0.39	0.31	0.37
$p_{95}[C_{glb}]$	291	302	289	296

B. *Optimisation and Sensitivity Results*

The sensitivity of the expected cost and ENS to generators sizes and positions is quantified using a variance-based method [16]. This first order Sobol's indices, $S_i = \frac{\mathbb{V}ar[\mathbb{E}[y|x_i]]}{\mathbb{V}ar[y]}$, (i.e. relative changes in outputs variances fixing decision variables one-at-a-time) are obtained by sampling uniformly 25000 random realisations from the design space. Each realisation is a vector of 64 elements, the first 32 contain the number of electric power DGs installed in $\mathcal{G}_{el}$ (4 for each of the 8 electric nodes) and the last 32 contain the number of HPs allocated within $\mathcal{G}_{th}$. The number of PVs and STs for each node is assumed to be constrained between 0 and 10, whilst other generators can vary between 0 and 2. The expected cost and expected ENS have been estimated using the Monte Carlo OPF method for each realisation. The first order Sobol's indices for $\mathbb{E}[ENS]$ and $\mathbb{E}[C_{glb}]$ are presented in top and bottom panel of Fig.3, respectively. It can be observed a sensitivity of the grid reliability to the allocation of wind

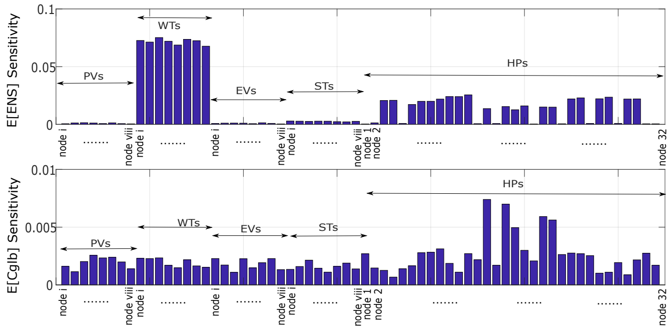

Fig. 3. The first order sensitivity indices S_i for the expected ENS (top panel) and expected cost (bottom panel).

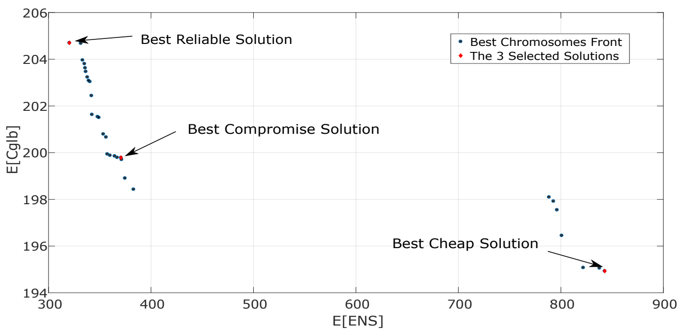

Fig. 4. The 3 best chromosomes selected among the best front in the generation of the NSGA-II procedure.

TABLE III
THE LOW COST, HIGH RELIABILITY AND COMPROMISE INVESTMENT SOLUTIONS

Solution	**Reliable**	**Compromise**	**Cheap**
$\mathbb{E}[ENS]$	320	370	842
$\mathbb{E}[C_{glb}]$	205	200	195
$C_V[ENS]$	1.55	1.46	0.79
$p_{95}[ENS]$	1302	1578	2520
$C_V[C_{glb}]$	0.27	0.29	0.42
$p_{95}[C_{glb}]$	287.1	284.3	301.1

turbines and heat pumps. Other generators seem to be less relevant, probably due to the smaller power output capacity and the limited modularity allowed within this analysis (e.g. max 10 PVs and 10 STs).

The NSGA-II optimisation procedure starts by selecting N_{pop}, N_{gen} and N_{MC} set to 500, 50 and 2000, respectively. Each chromosome decision vector is, in this case, a list of 64 integers which indicate the amount and type of distributed generators allocated in each node. The fitness of the best chromosomes evaluated within the last generation are displayed in Fig.4. The y-axis contains the $\mathbb{E}[ENS]$ and the y-axis $\mathbb{E}[C_{glb}]$; the 'best reliable' solution, the 'best cheap' solution and a compromise solution (average cost and reliability) have been selected and displayed with red diamond markers in Fig.4).

VI. Discussion and Conclusion

A stochastic framework for simulations and analysis of coupled electric power and heating networks has been presented. A probabilistic model is described which allows realistic weather-operational scenarios to be generated. A Monte Carlo OPF simulator is used to quantify reliability and cost of 4 investment scenarios on the Barry Island power-heat network. The results suggest that a combined investment on renewable heat and electric power generators provides greater benefits for the system reliability, and for a moderate cost due to available incentives. Sensitivity analysis pointed out that installation of wind turbines and heat pumps are affecting most the system reliability. To conclude, a set of good sizes and positions for HPs and DGs has been obtained thanks to a stochastic optimisation strategy.

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