Multi-Objective Optimisation of an Active Distribution System using Normalised Normal Constraint Method

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***Abstract*—An increasing implementation of renewable sources and electric vehicles can be of help in reducing the total operational cost of a power system, affecting power system technical operation. To this end, a multi-objective optimisation method using Normalised Normal Constraint (NNC) is applied in this paper by which two competitive objectives are considered: Minimisation of Active Distribution System (ADS) operational cost and minimisation of ADS power losses. Meanwhile, the uncertain behaviour of wind, photovoltaic units, and arrival and departure time of electric vehicles are considered. The proposed model is a multi-objective problem which comprises two stochastic stages and is simulated under GAMS environment on a modified IEEE 18-bus test system. The results clearly represent the trade-off between economic and technical benefits of the considered ADS. Furthermore, the effect of electric vehicles charging and discharging tariffs on the operational cost of the system are shown.**

***Index Terms*—Multi-objective optimisation, Normalised Normal Constraint (NNC), active distribution system, stochastic programming, renewable energy source, electric vehicle.**

NOMENCLATURE

A. *Indices*

$\boldsymbol{e}$	Index for batteries
$\boldsymbol{g}$	Index for distributed generations
$\boldsymbol{i,j}$	Index for nodes
$\boldsymbol{pv}$	Index for photovoltaic units
$\boldsymbol{s}$	Index for scenarios
$\boldsymbol{t}$	Index for time
$\boldsymbol{wt}$	Index for wind units
$\boldsymbol{\Lambda}$	Index for electric vehicles

B. *Parameters*

$L^P_{i,t}/L^Q_{i,t}$	Active/Reactive load, node i, period t
S_{ij}	Apparent power, line between nodes ij
Y_{ij}	Admittance magnitude of line between nodes ij
φ_{ij}	Phase angel of line between nodes ij
ζ_Λ	Efficiency for EV Λ
σ_Λ	Active power bid, EV Λ
Ψ^{epd}_Λ	Expected coefficient of EV Λ

C. *Variables*

$P_{\blacksquare,s\,t}$	Active power, unit $\blacksquare$, scenario s, period t
$Q_{\blacksquare,s\,t}$	Reactive power, unit $\blacksquare$, scenario s, period t
$SE_{\Lambda,st}$	Stored energy, EV Λ , scenario s, period t
$u_{\blacksquare,st}$	Binary variable of $\blacksquare$ (1=charge for batteries and EVs/on for DGs, 0=discharge for batteries and EVs/off for DGs)
$V_{\mathrm{i,st}}$	Voltage magnitude, node i, scenarios s ,period t
$\theta_{\mathrm{i,st}}$	Voltage magnitude, node i , scenario s, period t

Superscript max/min and C/D with any of above symbols present the maximum/minimum value and charge/discharge of the corresponded symbol. Moreover, Set $\blacksquare$ runs from 1 to $N_\blacksquare$

I. INTRODUCTION

Traditionally, a distribution network is a passive network, which is controlled by a distribution network operator where Distributed Generations (DGs) have been operated with a fit-and-forget method and demands are inflexible. On the other hand, the transition to Active Distribution System (ADS) provides more flexibility to control of DGs and demands in the distribution system [1]. Having said that increasing utilization of DGs, particularly Renewable Energy Sources (RES) such as Photovoltaic units (PV) coupled with high penetration of Electric Vehicles (EVs) in the distribution system brings challenges for the system operators, including tackling with their intermittent nature and their lack of inertia [2, 3].

To this end, several academic works have investigated the presence of RESs and EVs in the power system from different points of view. By way of illustration, a tri-level optimisation of an ADS is presented in [4], where different RESs are considered. In this work it was proposed that dispatchable DGs such as gas turbines can be of help in facilitating of integrating intermittent RESs. A two-stage stochastic programming is applied by [5] for capturing the uncertainty of wind and PV units. The proposed framework in this work led into decreasing of renewable energy curtailment and alleviating of energy imbalance because of the intermittent nature of RESs. The push towards sustainability and greener world has resulted in the substituting of fuel-based vehicles with EVs as they contribute significantly in reduction of emissions and environmental concerns [6].

An optimisation framework is presented in [7] where EVs are only capable of charging. In this work, EV charging rates were optimized in a way that their corresponding costs were minimized and keep the voltage profile of the system within the plausible range. The effect of State-Of-Charge (SOC) on the optimal operation of EVs and their contribution to an ADS is discussed in [8]. In this work, an energy management framework was proposed which led to improve the flexibility of ADS operation with assist of using EVs. Integration of EVs in power system causes a significant uncertainty which can be captured by Normal and Weibull probability distribution function. This view is shared and applied by [9].

The focus of mentioned articles is mostly fall into the minimization (maximization) of cost (revenue) though the technical aspects of operation such as operating within the acceptable voltage range or at the minimum power losses are important. It can be said that the optimal operation problem is not a pure single objective as other objectives such as having minimum power losses come to the fore and lead to forming a multi-objective problem. Several approaches have been used in literatures for solving a multi-objective problem among which heuristic methods are used by [10-13] and numerical optimisation-based methods are implemented by [14-16].

According to [17] numerical optimisation methods are more reliable than heuristic methods as the latter may being stuck in a local optimal area and do not guarantee to approach the global optimal solution in some cases. Many methods for solving a multi-objective problem can be integrated to obtain a single Pareto solution though a few of approaches such as Normal Boundary Intersection (NBI), Normalized Normal Constraint (NNC) and Directed Search Domain (DSD) methods are able to generate the whole Pareto frontier. The NNC method is a powerful and efficacious numerical optimisation-based method which is suitable for the two-objective problems [18].

For instance, a multi-objective reactive power optimisation of an AC-DC power system using piecewise NNC is used in [19]. In this work, voltage deviation and power losses are considered as objectives and the results showed a good distributions of Pareto solutions. Another example is [20] that the advantages of using NNC method in transmission congestion management is discussed. The virtues of using NNC method in this work highlighted as efficacious covering of the objective space via well-distributed Pareto solutions.

The main contributions of the current article can be highlighted as follows.

- Proposing a centralized energy management framework for an ADS with the aim of optimizing ADS operation.
- Investigating the trade-off between the competing objectives (ADS operational cost and power losses) according to the operator priorities and preferences, based on the Pareto optimal solutions using NNC method.
- Scrutinizing the impact of charging and discharging tariff of EVs and their expected SOC on the operational costs of the ADS.

The remainder of the paper is organized as follows. Problem formulation is presented in Section II. Section III discusses the solution algorithm. Numerical results for the proposed model are given in Section IV, and the conclusion is provided in Section V.

II. Modelling and Formulating the Problem

A. *Centralized multi-objective optimisation framework*

The considered ADS consists of various dispatchable units, RESs, and loads. ADS can transact in the electricity market and buy/sell active power from/to the wholesale electricity market. Also, there are some EV parking slots in the ADS which provide the opportunities for the operator to utilize EVs capability when they are available in the defined parking slots.

In order to take the advantages of EVs on the operation and security of the network, it is efficient to integrate EV’s energy management with ADS operation.

To this end, a centralized energy management framework is considered to co-optimize ADS operation and EVs energy management.

In the considered centralized energy framework, it is assumed that EV’s aggregators send EVs information to the operator in the day-ahead period through communication links. This information consists of the forecasted arrival and departure times, EV’s forecasted SOC at the arrival time and the expected SOC at the departure time. Based on the received data, system operator can manage the EVs energy while is subjected to fulfil their expectations.

The considered multi-objective optimisation problem in this paper is a mixture of two competitive technical and economic aims, including minimisation of operational cost and minimisation of power losses. In this paper. They are given in (1) and details are provided in Section II.B.

$$Objectives = \begin{cases} f^{Cost}, operational\ cost \\ f^{Loss}, power\ losses \end{cases} \tag{1}$$

Operational cost is an economic objective and the power losses is a technical one. Considering these objectives, problem can be discussed from two perspectives as follows. In this context, operator must consider its assets and opportunities such as committing the cheaper units and integrating of EVs. On the other hand, operator prefers less power losses in its network.

Hence, operator is encountered with two competitive objectives that must be co-optimized. Indeed, optimal solution of MG operation will be attained by trade-off between objectives according to operator's preferences.

Generally speaking, the proposed centralized multi-objective optimisation framework consists of three steps. First, information of EVs, market price and ADS's asset are sent to the operator. Second, the centralized optimisation is applied by operator to solve the problem using NNC method. Third, optimal scheduling of EV's charging/discharging, and ADS's distinct asset are determined.

B. Problem Formulation

In this paper, ADS's asset comprises dispatchable DGs such as gas turbines and steam turbines, batteries, and uncertain sources such as wind turbines, and PV units. The cost of DGs are indicated in (2).

According to [25], cost function of active and reactive power for different operation regions of DGs are modeled as a quadratic function. In order to avoid modulus function in (2), it converted to a linear function using duality method [17].

DGs technical constraints (e.g. maximum/minimum capacity, maximum/minimum up/down time) are considered [4],[21]. Furthermore, batteries are modelled according to [4] and their degradation costs($Cost_s^e$) are considered. It is worth mentioning that transaction in the market is neglected here for simplicity.

$$Cost_s^{DDG} = \sum_{g=1}^{N_g}\sum_{t=1}^{N_t} A_g(P_{g,st})^2 + B_g P_{g,st} + C_g\, A'_g\left|Q_{g,st}\right|^2 + B'_g\left|Q_{g,st}\right| + C'_g \quad (2)$$

For modelling renewable sources, including wind and PV units, the model of [4] has been implemented here. Some assumptions are contemplated for modelling EVs.

Firstly, they can operate in either charging or discharging modes and this cannot happen simultaneously. In addition, once they are connected to the ADS, the operator can control their charging/discharging modes.

Next, EVs have individual owners and consequently the behavior of each EVs in arriving and departing of parking slots are determined by them which causes a stochastic behaviour. Having said that, Normal distribution function can be used in large-scale problems where the number of EVs are considerable and is implemented here to capture the uncertainty in arrival and departure time of EVs [2].

Moreover, EVs need to be charged to their likely SOC at their departure time. The cost (revenue) of charging(discharging) EVs is illustrated in (3). The charging/discharging of EVs are subjected to (4). Energy balance of EVs are demonstrated in (5). Storage capacity limits of EVs is presented in (6). Finally, (7) shows the SOC fulfillment of EVs at their departure time.

$$Cost_s^{EV} = \sum_{t=1}^{N_t}\sum_{\Lambda=1}^{N_\Lambda}\left[\sigma_\Lambda^D P_{\Lambda,st}^D - \sigma_\Lambda^C P_{\Lambda,st}^C\right] \quad (3)$$

$$0 \le P_{\Lambda,st}^C \le P_\Lambda^{C,max} \times u_{\Lambda,st} \quad (4.a)$$

$$0 \le P_{\Lambda,st}^D \le P_\Lambda^{D,max} \times (1 - u_{\Lambda,st}) \quad (4.b)$$

$$P_{\Lambda,st} = P_{\Lambda,st}^C + P_{\Lambda,st}^D \quad (4.c)$$

$$SE_{\Lambda,st} = SE_{\Lambda,s,t-1} + \zeta_v^C P_{\Lambda,st}^C \Delta t - \frac{1}{\zeta_\Lambda^D} P_{\Lambda,st}^D \Delta t \quad (5)$$

$$SE_\Lambda^{min} \le SE_{\Lambda,st} \le SE_\Lambda^{max} \quad (6)$$

$$SE_{\Lambda,st} = \Psi_\Lambda^{epd} SE_\Lambda^{max} \qquad \forall t = t_\Lambda^{departure} \quad (7)$$

Active and reactive power balance equations are illustrated in (8) and (9), respectively. Maximum apparent power of lines and maximum/minimum voltage of buses are indicated in (10).

$$\sum_{g=1}^{N_g} P_{i,g,t} + P_{i,wt,st} + P_{i,pv,st} + \sum_{\Lambda=1}^{N_\Lambda} P_{\Lambda,st} + \sum_{e=1}^{N_e}\left(P_{i,e,st}^D - P_{i,e,st}^C\right) - L_{i,t}^P = \sum_{j=1}^{N_j} V_{i,st} V_{j,st} Y_{ij}.\cos\left(\theta_{i,\mathrm{st}} - \theta_{j,\mathrm{st}} - \varphi_{\mathrm{ij}}\right) \quad (8)$$

$$\sum_{g=1}^{N_g} Q_{i,g,t} - L_{i,t}^Q = \sum_{j=1}^{N_j} V_{i,st} V_{j,st} Y_{ij}.\sin\left(\theta_{i,\mathrm{st}} - \theta_{j,\mathrm{st}} - \varphi_{\mathrm{ij}}\right) \quad (9)$$

$$P_{ij,st}^2 + Q_{ij,st}^2 \le \left(S_{ij}^{max}\right)^2 \quad (10.a)$$

$$V_i^{\min} \le V_{i,\mathrm{st}} \le V_i^{\max} \quad (10.b)$$

Finally, the multi-objective formulation is represented in (11), where the economic and technical parts are provided in (12) and (13), respectively. The aim of (11) is minimising two objectives simultaneously.

$$Objective\ Function\text{: } min\ F(f^{Cost}, f^{Loss}) \quad (11)$$

$$f^{cost} = \sum_{s=1}^{N_s} \pi_s\left(Cost_s^{DDG} + Cost_s^{EV} + Cost_s^e\right) \quad (12)$$

$$f^{Loss} = \sum_{s=1}^{N_s} \pi_s Loss_s^{Apparent} = \sum_{s=1}^{N_s} \pi_s \sqrt{(Loss_s^{Active})^2 + (Loss_s^{Reactive})^2} \quad (13)$$

III. Solution Algorithm

The proposed model is a two-stage stochastic programming problem which is explained as follows. Furthermore, the NNC method is discussed briefly too.

A. Uncertainty Stages

The scenario set in the proposed model comprises the stochastic nature of RESs, including wind and PV units and the stochastic behaviour of EVs in arriving and departing the parking slots. Notably, the output power of dispatchable DGs should be specified before determination of uncertain stochastic sets. In other words, dispatchable DGs are here-and-now decisions and they are independent from the scenario realisations.

Other variables such as batteries charging/discharging are wait-and-see variables. In order to generate a meaningful set of possible scenarios, Latin Hypercube Sampling (LHS) [22] technique is applied following by the Kantorovich distance [23] method as an effective mean for scenario reduction. In this paper, uncertain behaviors of wind turbine and PV power, and the uncertainty in the arrival and departure time of EVs are considered.

B. Normalised Normal Constraint Method

By and large, optimal solutions of a multi-objective problem are named Pareto optimal solutions. In this paper, in order to generate Pareto solutions, NNC method is applied. Generally, there are three main advantages for this method:

1- For a two-objective optimisation problem it can search the entire solution space and does not neglect any region [18] which means that all regions of the solution space are adequately represented in the generated solutions.

2- The generation of Pareto points is performed in the normalized objective space, which results in critically beneficial scaling properties [26]. This normalized space has the desirable property that performance of the method is entirely independent of the objectives' scales.

3-The NNC produces a Pareto optimal with a regularly distributed set of points, even distribution of Pareto solutions is an indication that the solution space is well represented in the Pareto points [26].

In NNC method, at first, solution space is normalized (Fig. 1a). Next, *Anchor* points (Fig. 1b) are generated, these points are obtained when each of objective in multi-objective problem is minimized independently. *Anchor* points also are the end points of *Pareto frontier* (Fig. 1b). In the two-objective problem, the line that connects two *Anchor* points to each other is named *Utopia line* (Fig. 1b). Second, *Utopia point* (Fig. 1b) are produced that are distributed points on Utopia line.

Finally, in order to find each Pareto optimal point according to each Utopia point, *Normal line* is generated. This line intersects the *Utopia line* in *Utopia point* and also is perpendicular to *Utopia line*. Normal line is applied to produce an inequality constraint which is used as an additional constraint that progressively reduces the feasible region which must be searched to find optimal solution (Fig.1 c) [26].

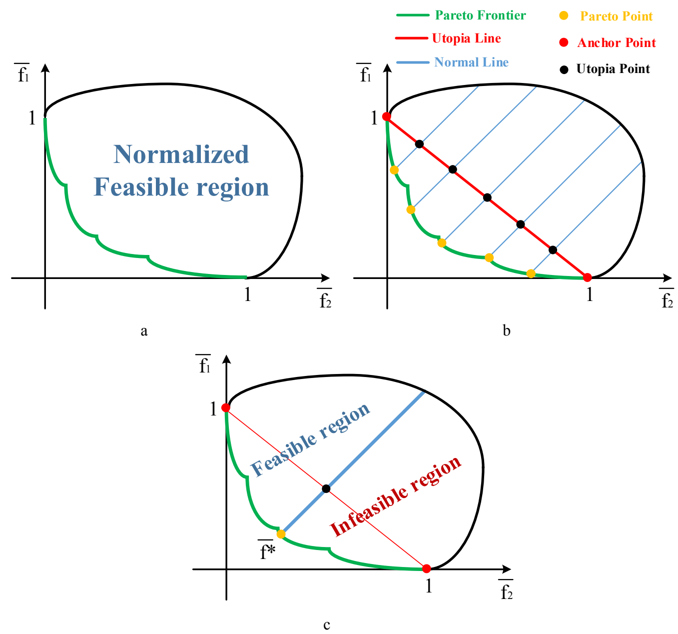


Fig. 1. Representation of the Normalized Normal Constraint Method for two-Objective Problem

IV. NUMERICAL RESULTS AND DISCUSSIONS

A modified 18-bus IEEE test system is employed as the case study to demonstrate the effectiveness of the suggested framework.

Finally, the optimisation problem is formulated in GAMS environment [2]. For solving the MINLP problem, DICOPT solver has been used. To guarantee accuracy and feasibility of solutions in GAMS, two important parameters exist whose values can be determined by user. 1- OPTCR: Relative optimality criterion and 2-OPTCA: Absolute optimality criterion.

These attributes specify a relative termination tolerance and absolute termination tolerance for solving mixed-integer models, respectively. In this paper, OPTCR is considered 10^{-6} and OPTCA is considered 0.

As the proposed model is a stochastic problem, all the values which are indicated in figures and tables are the expected values.

A. Two-objective optimisation analysis

In this section, two-objective optimisation of an ADS is investigated. Fig. 2a shows the cost and apparent losses of the considered ADS in all Pareto points that have been attained using NNC method. It can be seen that two objectives behave oppositely against each other, increasing of operational costs leads to reduction in the apparent power losses and vice versa. Fig. 2b represents the cost versus apparent power losses in Pareto points. Indeed, this figure shows the trade-off between cost and apparent losses. According to the preferences and priorities of decision maker, optimal point would be different. In fact, considering the importance of each objective from operator's perspective, the suitable operating point would be determined.

According to Fig. 2b, from point 1 to point 15, power losses has a decreasing trend. This trend indicates that importance of loss increases gradually in comparison with operational cost and at point 15, the most priority dedicates to the power losses.

B. Cost analysis

In order to analyse the effect of different elements on the operational cost, three cases are considered. Case1 indicates the normal operation of the network in which all the elements are available. In Case2, EVs are not considered, and Case3 is without RESs. Table 2 illustrates the results of each case. According to Table 2, the operational cost in Case2 is more than case1 which is the result of lacking EVs and has two main reasons.

First, in the absence of EVs, network does not have this opportunity to sell power to EVs and get benefits. Second, network loses the opportunity to exploit arbitrage opportunity of EVs' batteries. In Case3 which renewable energy resources are neglected, the operational costs increase in comparison with other cases, owning to the fact that the operational costs of RES are neglected in this paper. As DGs are the only resources for providing reactive power, the cost of supplying reactive power does not change significantly in the mentioned cases. In addition, in Case 2 and Case 3 which EVs and RES are eliminated respectively, batteries are used more than Case 1 as their costs are less than other DGs.

C. EV analysis

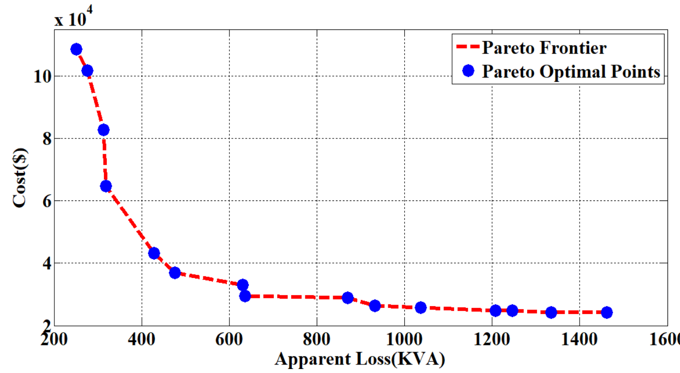
In this section, impact of charge/discharge tariff ratio and EV owner's expectation on the operational cost is investigated. Cases 1, 2 and 3, indicate ratio of discharge to charge tariff of which are considered 1.1, 1.15 and 1.2, respectively.

Table 3 represents the results of cases. According to Table 3, by increasing this ratio, the benefits of using EVs decreases because the operator must pay more to provide active power from EVs. In Cases 4, 5, and 6, operator is obliged to charge EVs' battery 100%, 90% and 80% of their maximum capacity, respectively at their departure time. The results of mentioned cases are indicated in Table 4. According to Table 4, decreasing of EVs expectation, network would have this opportunity to charge/discharge EVs battery capacity in a more flexible way which leads to get more benefit.

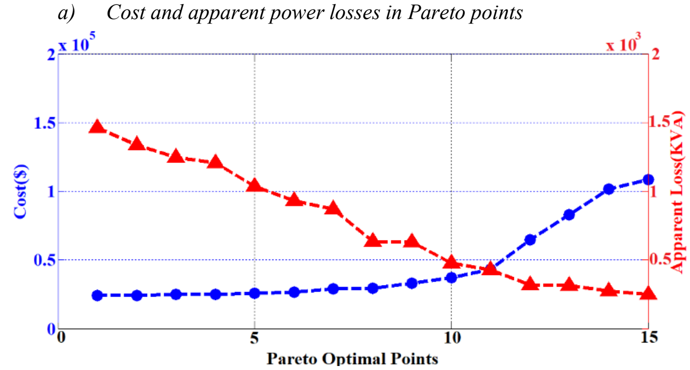
D. Further Discussion

Recently, some literatures [6, 24, 25] discussed the possibility of providing reactive power by EVs which is an optimistic and maybe unrealistic to some extend from the industry points of view. However, they show that for example EVs can contribute in improvement of voltage and reducing power losses via providing reactive power to the grid [24]. As a future work, the pros and cons of providing reactive power through EVs for an ADS will be scrutinised. In addition, apart from the economic and technical objectives, an environmental objective can be considered to show the significance impact of using EVs in pollution reduction. Further research contributes to the physical correlation of EV's arrival and departure time and different probability distributions.

Having said that the reason of using Normal distribution which is used in this paper is supported by several reasons (e.g., from the mathematical and computational points of view is easy to work with) [24]. Further research can contribute to accommodate the proposed model on the larger test systems.



a) *Cost and apparent power losses in Pareto points*



b) *Cost versus apparent power losses*

Fig. 2. Two-objective optimization

TABLE I: IMPACT OF DIFFERENT COMPONENTS ON THE OPERATIONAL COST

	Operational Cost ($)	P_{PEV} ($)	P_{DG} ($)	Q_{DG} ($)	Battery ($)
Case1	36905	-670	32494	5069	12
Case2	37743	0	32652	5076	15
Case3	39218	-657	34916	4930	29

TABLE II: IMPACT OF CHARGE AND DISCHARGE TARIFF RATIO

	Operational Cost ($)	P_{EV} ($)
Case1	36918	-670
Case2	36986	-605
Case3	37077	-537

TABLE III: IMPACT OF SOC EXPECTATION AT THE DEPARTURE TIME

	Operational Cost ($)	P_{PEV} ($)
Case4	36918	-670
Case5	36812	-726
Case6	36757	-789

V. CONCLUSION

A bi-objective optimisation problem was proposed which considered two competitive objectives: minimisation of the operational cost and the minimisation of ADS power losses. The NNC method has been applied for solving the problem. The uncertainty associated with wind and PV units was considered. Furthermore, stochastic behaviour of EVs was modelled. Finally, the proposed model, a bi-objective optimisation problem with two stochastic stages, was solved using GAMS on a modified 18-bus IEEE test system. Results were analysed from three perspectives: first, the trade-off between cost and power losses showed that they are in direct contradiction with one another (i.e. a decrease in one leads to an increase in the other). Second, the effect of each ADS component on the total operation cost of ADS has been investigated and concluded that the most expensive case is without RES. Finally, the impact of EVs charging and discharging tariffs and their expected SOC have been scrutinized. It has been shown that the less the expected SOC of EVs is, the more ADS can gain benefits.

ACKNOWLEDGEMENTS

Mohamed Lotfi and João P. S. Catalão acknowledge the support by FEDER funds through COMPETE 2020 and by Portuguese funds through FCT, under 02/SAICT/2017 (POCI-01-0145-FEDER-029803).

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