AN OPTIMISATION MODEL TO INTEGRATE ACTIVE NETWORK MANAGEMENT INTO THE DISTRIBUTION NETWORK INVESTMENT PLANNING TASK

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ABSTRACT

This paper presents a novel mathematical optimisation model to assist with decision-making in the distribution network investment planning task, and more specifically when Active Network Management (ANM) schemes are deployed. The objective of the task is to find a least-cost network investment strategy, taking into account traditional reinforcement and up-rating of network assets alongside the deployment of ANM schemes as investment decisions. The problem is initially modelled as a complete mixed-integer program, before Benders decomposition is applied to divide the original problem into a binary investment problem and two operational sub-problems. Stochastic programming techniques are used to incorporate the uncertain nature of intermittent generation and demand when calculating operational costs over the planning period.

INTRODUCTION

As the electricity supply industry in the UK advances to meet challenging environmental targets, many Distribution Network Operators (DNOs) are witnessing an increase in the level of Distributed Generation (DG) integration, often generation which harnesses energy from intermittent renewable sources such as wind (with some marine/tidal generation emerging). In some areas such connections are resulting in the development of capacity bottlenecks on distribution networks with topologies which were not initially designed to accommodate significant levels of generation. Traditionally, such a constraint would be overcome through the reinforcement and up-rating of network assets such as circuits and transformers. However, the conservative "worst-case scenario" planning paradigm from which network capacity is determined can result in a network where capacity limits are rarely reached. The inclusion of stochastic elements in networks such as intermittent DG output further accentuates the miscalculation of required or desired network capacity.

Specific forms of Active Network Management (ANM) schemes provide network planners with an alternative to the expensive reinforcement of network assets, through the real-time monitoring and control of power flow at bottlenecks [1]. In the event that a circuit is reaching its thermal limit, participating DG units can curtail their output to eliminate the network constraint in exporting circuits. The deployment of such schemes encourages a rethink of the current 'fit-and-forget' planning approaches, and drives the formulation of novel planning methodologies accurately represent the new dynamic operational characteristics of "active" networks.

The optimisation approach presented in this paper integrates emerging ANM schemes and their features into a simplified network investment optimisation model. Uncertainty is taken into consideration through the treatment of customer load and intermittent DG output as stochastic parameters, using stochastic programming techniques to incorporate uncertainty into the model.

REQUIREMENTS FOR ACTIVE NETWORK PLANNING

The optimisation of network investment planning is conventionally interested in finding a minimum cost investment strategy which results in a network which can accommodate forecasted generation and demand growth while ensuring a secure supply of electricity. Traditionally, network investment within optimisation models is the reinforcement and up-rating of network assets, notably circuits and transformers.

As new solutions such as ANM schemes emerge as alternatives to traditional reinforcement, there is a need to update investment planning models, introducing ANM deployment as a new investment decision within the optimisation. From a network capacity perspective, the deployment of ANM with DG effectively removes the units from any network capacity calculations and limits, as the DG can fully curtail its output, therefore not contributing to thermal constraints.

Furthermore, the introduction of ANM deployment decisions to the optimisation problem establishes new financial functions within the model. Although the capital cost of deploying ANM solutions is significantly lower than traditional reinforcement it introduces an occasional operational cost; compensation payment to the DG developer for lost revenue through energy curtailment. The overall significance of this cost is dependent on the frequency and severity of energy curtailment on the network, which will be related to the scale of DG connected on the network. The key challenge in planning active networks is determining the level of DG penetration at which it is financially beneficial to invest in network reinforcement (at a greater cost) but provide DG a "firm" connection, or to deploy ANM solutions and control power flows in real-time, potentially incurring higher operational costs.

Introducing uncertainty

The incorporation of ANM deployment within a network investment optimisation model requires a method for determining the operational cost over the planning period. As potential curtailment at any point in time is dependent on the specific generation and demand levels at that moment, uncertain parameters can be expressed as stochastic variables. Stochastic programming techniques split the optimisation model into 2-stages; a first-stage 'here-and-now' investment decision, followed by finding the expected value of the second-stage operational problem, which contains the new stochastic variables [3]. A Monte-Carlo method is used to solve the expected value of the operational problem, by taking a large number of samples from the probability distribution functions (pdf) of the stochastic variables, and the operational problem is solved for each set of samples [3]. Furthermore, there are many similarities between decomposition approaches for Stochastic programming problems and large Mixed-Integer Programs (MIP), of which there are many power systems optimisation examples [4,5]. The decomposition method is developed later in the paper.

NETWORK INVESTMENT MODEL

Full Mixed-Integer Program

The proposed optimisation model finds the minimum-cost investment strategy which results in a network capable of accommodating all DG connections, while meeting technical constraints. The objective function is:

$$\min \sum_{j\in J, r\in R} C_{j,r} x_{j,r} + \sum_{b\in\Psi_b} C_b^{ANM} u_b^{ANM} + \sum_{n\in N}\sum_{b\in\Psi_b} O_{b,n}^{ANM} y_{b,n}^{ANM} \quad (1)$$

The first term of (1) represents the cost of upgrading the capacity r of existing circuit branches j, triggered via binary decision variable $x_{j,r}$. The second term represents the cost of deploying ANM schemes at nodes b, with deployment decisions represented through the binary variable u_b^{ANM}. The final term is the operational cost of curtailment O_b^{ANM}, for each unit of energy curtailed y^{ANM} at sample n.

$$P_j^+ = \sum_{r\in R} x_{j,r} K_{j,r} \quad (2)$$

$$\sum_{r\in R} x_{j,r} \leq 1 \quad (3)$$

$$x_{j^+,r} = x_{j^-,r} \quad (4)$$

Constraints (2-4) are logical constraints associated with the binary investment decision variables. (2) updates the maximum capacity limit of circuit branches j following the investment decision $x_{j,r}$, with K the vector of potential capacity upgrades. (3) ensures that for all possible capacity upgrades K_r on each branch j, only one binary decision variable may be nonzero. In order to maintain linearity, each right-of-way must be represented as 2 separate branches, with positive-only flows in each direction, (4) verifies that both directions of each branch share the same investment decision variable, and thus capacity P_j^+.

$$G_b + \sum_{j\in J} I_{b,j}^{Br} P_j + I_b^{GSP}\left(P_b^{GSP} - P_b^{RGSP}\right) - P_b^{loss} - v_b^{ANM} - L_b = 0 \quad (5)$$

$$P_j - B_j(\delta_k - \delta_b) = 0 \quad k, b \in \Psi_b \quad (6)$$

Constraints (5) and (6) represent Kirchoffs Current Law (KCL) and Kirchoffs Voltage Law (KVL) respectively. KCL holds if all power flows into a node equals all power flow out of the node. The representation above takes into account the following nodal parameters; DG output; branch power flows in/out; GSP flows in/out; Power losses; ANM curtailment; and load. I^{Br} denotes the branch-node oriented incidence matrix, and I^{GSP} an incidence matrix which identifies what nodes represent the GSP link to the transmission network. Power losses are calculated linearly using piecewise approximation.

$$P_j^- \leq P_j \leq P_j^+ \quad (7)$$

$$P_b^{GSP^-} \leq P_b^{GSP} \leq P_b^{GSP^+} \quad (8)$$

$$P_b^{RGSP^-} \leq P_b^{RGSP} \leq P_b^{RGSP^+} \quad (9)$$

$$\delta_b^- \leq \delta_b \leq \delta_b^+ \quad (10)$$

$$G_b^- \leq G_b \leq G_b^+ \quad (11)$$

$$L_b^- \leq L_b \leq L_b^+ \quad (12)$$

$$\delta_b \leq M(1 - I_b^{GSP}) \quad (13)$$

$$0 \leq v_b^{ANM} \leq u_b^{ANM} G_b \quad (14)$$

$$0 \leq y_b^{ANM} - v_b^{ANM} \leq G_b\left[1 - u_b^{ANM}\right] \quad (15)$$

(7-12) represent the capacity limits of branch flow, GSP capacity (in both directions), voltage angle, DG output, and demand. (13) ensures the voltage angle at the reference bus is zero. (14,15) introduce a new variable which represents the product of ANM variables $u_b^{ANM} y_b^{ANM}$, ensuring DG units can only be curtailed following the deployment of an ANM scheme, when the binary investment variable is nonzero. These constraints maintain linearity as they avoid a product of two decision variables in (5).

Model Decomposition

The structure of the model previously described makes it relatively straightforward to decompose into smaller sub-models. The initial problem contains complicating variables, i.e. decision variables which when fixed make the remaining problem simpler to solve. As the problem has a natural 2-stage structure of investment decisions and operational decisions, Benders decomposition method can be applied [4]. This technique separates the full problem into two or more smaller sub-problems, which are solved independently, and information regarding feasibility and global optimality is shared between sub-models through coupling constraints which are referred to as Benders cuts.

This particular model is decomposed as follows; the 'here-and-now' investment decisions and related constraints form the **master problem**, the objective function of which includes an underestimation of the operational costs. In most cases of Benders decomposition, only one additional *slave* sub-problem exists. However, due to the large number of instances of stochastic Monte-Carlo sampling which must take place to determine operational cost, two *slave* sub-problems will be used, with the aim of decreasing the solution time of the model [5]. The deterministic **capacity sub-problem** performs a DC load flow at peak generation/load conditions to ensure all flows are within capacity limits, if ANM investment has been made at a DG unit, it is discounted from the load flow as full curtailment will be possible during constrained scenarios. The **operation sub-problem** calculates the expected value of the operational costs (compensation cost of energy curtailment), once the network investment meets capacity requirements. A modified OPF is used to find the optimal curtailment strategy to prevent overloads if necessary. *N* instances of the OPF are simulated, as the stochastic parameters take on values sampled from probability distributions in each OPF instance.

The Benders algorithm is an iterative procedure, illustrated in Figure 1. Following the solution of each slave sub-problem, the Benders cuts which are generated and added to the master problem provide the master with information on what investments will further reduce the value of the slave solution. The solution of the master problem at the iteration is an underestimation of the global solution and is referred to as the lower bound. The upper bound is the final cost of investment and operation calculated once all sub-problems have been solved. These bounds are updated at each iteration of the process. Once both bounds are within a pre-defined tolerance of each other, an optimal solution has been found [5].

Master Problem

The master problem (16) is concerned with finding the optimal 'here-and-now' investment decisions:

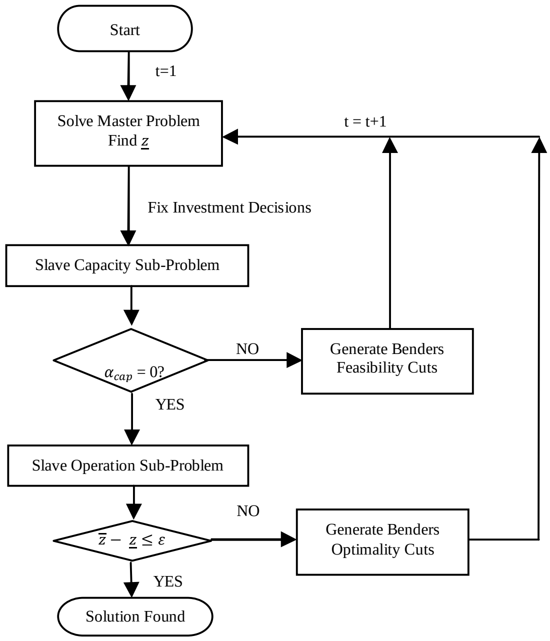

Figure 1: Benders Decomposition Algorithm

$$\min \underline{z} = \sum_{j\in J, r\in R} C_{j,r} x_{j,r} + \sum_{\Psi_b} C_b^{ANM} u_b^{ANM} + \alpha \qquad (16)$$

Which is subject to the investment constraints (2)-(4). The α function represents an estimate of the operational costs, and is defined as Benders cuts are added to the master problem later in the process.

Capacity Sub-Problem

The first slave sub-problem is responsible for verifying the security of the network investment decisions made in the master problem. A modified DC load flow checks that there is sufficient power-flow capacity on the network to accommodate generation while meeting demand. In this example, the security is checked at a max generation/max demand scenario, though many security scenarios may be verified. To ensure the sub-problem will solve, an unbounded slack variable S_b is introduced at each node, which can reduce branch flows, guaranteeing that capacity constraints will always be met. Naturally, the object of this sub-problem is to minimize the total value of slack energy to zero. At this point an investment strategy which meets the security requirements of the network has been identified.

The Objective function of the Capacity Sub-Problem is:

$$\min \ \alpha_{cap} = \sum_{b\in\Psi_b} S_b \qquad (17)$$

Subject to constraints (6-10), (13), and modified nodal current constraint:

$$G_b^+ \left(1 - U_b^{ANM}\right) + \sum_{j \in J} I_{b,j}^{Br} P_j + I_b^{GSP}\left(P_b^{GSP} - P_b^{RGSP}\right) - P_b^{loss} - L_b^+ - S_b = 0 \quad (18)$$

Constraints (19) and (20) are added to fix the values of investment decision variables from the **master problem**. The dual values $\pi_{j,r}$ and π_{ANM} are established, which provide information on the sensitivity of the investment decisions solved in the master problem. The value of the dual variable illustrates the effect a change in the binary variables will have on the cost of α_{sec}.

$$X_{j,r} = x_{j,r} : \pi_{j,r} \quad (19)$$

$$U_b^{ANM} = u_b^{ANM} : \pi_{ANM} \quad (20)$$

In the case of α_{cap} being non-zero, constraint (21) is added to the master problem, such constraints are known as Benders feasibility cuts. The Benders feasibility cuts improve the decisions to be made in the master problem during the next iteration of the process, improving the optimality of the following slave sub-problems.

$$\alpha^{t-1} + \pi_x^{t-1}\left(x_{j,r}^t - x_{j,r}^{t-1}\right) + \pi_u^{t-1}\left(u_{b,ANM}^t - u_{b,ANM}^{t-1}\right) \leq 0 \quad (21)$$

Operational Sub-Problem

The operational *slave* sub-problem performs an ANM-dispatch OPF which curtails ANM-enabled generators when thermal constraints occur (either transformer or circuit capacity limits are exceeded). The objective (22) of the OPF is to find the optimal curtailment strategy which will minimise the unnecessary energy lost.

Due to the uncertain nature of intermittent DG and demand, all loads and any wind DG are modelled as stochastic parameters. The sub-problem is solved for N instances, with values for the stochastic parameters sampled from their *pdf*.

$$\min \alpha_{op} = \sum_{n=1}^{N} \frac{1}{N} \sum_{b \in \Psi_b} O_b^{ANM} y_b^{ANM} \quad (22)$$

Subject to constraints (6-15), (19-20), and the nodal current constraint:

$$G_b + \sum_{j \in J} I_{b,j}^{Br} P_j + I_b^{GSP}\left(P_b^{GSP} - P_b^{RGSP}\right) - P_b^{loss} - v_b^{ANM} - L_b = 0 \quad (23)$$

Following the solution of α_{op} the upper bound $\bar{z}$ can be updated (24):

$$\bar{z} = \sum_{j \in J} C_j x_{j,r} + \sum_{b \in B} C_b^{ANM} u_b^{ANM} + \alpha_{op} \quad (24)$$

The solutions can be checked for optimality, where ε is a pre-set tolerance. Once the upper bound and lower bound are sufficiently close, optimality criterion has been met.

$$\bar{z} - \underline{z} \leq \varepsilon \quad (25)$$

In the event that the optimality criterion is not met, the following Benders optimality cut (26) is added to the Master problem and the iterative process is repeated until optimality is reached. The Benders optimality cuts provide the master problem at iteration *t* with the parameter α^t, an underestimation of the operational sub-problem cost at the current iteration.

$$\alpha^t \geq \alpha^{t-1} + \pi_x^{t-1}\left(x_{j,r}^t - x_{j,r}^{t-1}\right) + \pi_u^{t-1}\left(u_{b,ANM}^t - u_{b,ANM}^{t-1}\right) \quad (26)$$

CONCLUSIONS

The paper has described a new optimisation model for application to the distribution network investment task. Although the model presented is a simplified illustration of the real investment planning task, it demonstrates how the deployment of ANM can be integrated into established network optimisation models. In practise, when applied to distribution networks, an approach based upon simplified DC load flow equations will not produce a solution of sufficient accuracy, as voltage levels and reactive power flows are absent in the linearised DCLF calculations. To improve the model, the slave sub-problems must employ full AC load flow constraints, increasing the computational complexity of the problem as the slave sub-problems will be non-linear and non-convex.

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