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Implementing a model predictive control strategy on the dynamic economic emission dispatch problem with game theory based demand response programs

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ABSTRACT

In this paper, a game theory demand response program is incorporated into two problems; the dynamic economic emission dispatch problem and the price based dynamic economic emission dispatch problem. The game theory demand response program is an incentive based program which provides monetary incentives for willing customers who agree to curtail their demand, with the incentive greater than or equals to the their cost of curtailment. Both mathematical problems are multi-objective optimization problems and for the first model, the objectives are to minimize fuel costs and emissions and determine the optimal incentive and load curtailment for customers. The second model seeks to minimize emissions, maximize profits and also determine the optimal incentive and load curtailment for customers. Model predictive control, which is known as a closed loop approach from a control perspective is deployed to solve both proposed mathematical models and a comparison is provided with solutions obtained via an open loop approach. Obtained results validate the superiority of the closed loop approach over the open loop controller. For instance the closed loop approach yields 4.36 MWh and 11.35 MWh higher customer energy curtailments than the open loop approach for the first and second models respectively. Furthermore, obtained results also prove that the closed loop control approach shows better robustness against uncertainties and disturbance.

1. Introduction

The DEED problem is a multi-objective mathematical optimization problem with two conflicting objectives of minimizing fuel cost and emissions of thermal generators. The aim is to determine the optimal output of thermal generators under several practical constraints [1]. Some of the often considered constraints include: power balance constraints [2], ramp rate constraints, generator output limit constraints [3], line flow limit constraints, spinning reserve constraints [4], etc. The problem has received considerable interest by engineers and scientists alike due to increasing environmental consciousness and the need to curtail harmful emissions from thermal generators. In recent years, as many nations of the world have shifted from a regulated power system and embraced deregulation, this has given rise to the development of a new variant of the DEED problem. In this new variant, maximizing profit has replaced the former objective of minimizing cost. This has given birth to the PBDEED problem with the dual objectives of maximizing profit and minimizing emissions of thermal generators under the same or similar constraints as the DEED problem [5]. The DEED or PBDEED problem is solved depending on if it is in a regulated or deregulated climate. Another feature of modern power system operations is the drive or push to encourage a more responsible use of electrical power and minimization of electric power consumption. This has given rise to demand response programs. These programs are classified into two kinds: price based programs or incentive based programs.

In this work, we integrate a GTDR program which is an incentive based demand response program into the DEED and PBDEED problem. The resulting models determines the optimal output of thermal generator, optimal load to be curtailed by participating customers and the incentive to be paid to them. The resulting models are known as GTDR-DEED and GTDR-PBDEED. It has been shown in Ref. [6] that integrating DEED/PBDEED and demand response programs and solving the resultant integrated model

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Nomenclature

Sets and indices:

I	time
T	generators
J	customers

Variables:

$P_{i,t}$	power generated from generator i at time t
$x_{j,t}$	amount of power curtailed by a customer j at time t
$y_{j,t}$	incentive of a participating customer j at time t

Parameters:

C_i	fuel cost of generator i
E_i	emissions for generator i
D_t	total system demand at time t
$loss_t$	total system losses at time t
$P_{i,min}$ and $P_{i,max}$	minimum and maximum capacity of generator i
DR_i and UR_i	maximum ramp down and up rates of generator i
a_i, b_i and c_i	fuel cost coefficients of generator i
e_i, f_i and g_i	emission coefficients of generator i
$B_{i,k}$	ikth element of the loss coefficient square matrix of size I
EP_t	forecast energy price at time t
$K_{1,j}$ and $K_{2,j}$	cost function coefficients of customer j
UB	utilitys total budget
CM_j	daily limit of interruptible energy for customer j
$\lambda_{j,t}$	value of power interruptibility of customer j at time t.
θ_j	customer type
m	switching interval of the MPC controller
w_1, w_2 and w_3	objective function weights

List of abbreviations:

GTDR	game theory based demand response
SED	static economic dispatch
DED	dynamic economic dispatch
DEED	dynamic economic emission dispatch
PBDEED	price based dynamic economic emission dispatch
MPC	model predictive control
PBDR	price based demand response
IBDR	incentive based demand response
TOU	time of use rates
RTP	real time pricing
CPP	critical peak pricing
EDP	extreme day pricing
EDCPP	extreme day critical peak pricing
DLC	direct load control
IS	interruptible services
EDRP	emergency demand response programs
CMP	capacity market programs
DB	demand bidding/buyback programs
AMS	ancillary market services
ISO	independent system operator
PJM	Pennsylvania-New Jersey—Maryland
AIMMS	advanced interactive multidimensional modelling system
MADM	multi attribute decision making
MINLP	mixed integer non linear programming
CHP	combined heat and power
CSA	Cuckoo search algorithm
TLBO	teaching learning based optimization
BSA	backtracking search algorithm
CSADHS	chaotic self adaptive differential harmony search
NSGAII	nondominated sorting genetic algorithm II
FFA	hybrid fire fly algorithm
HS	harmony search
RE	renewable energy

yields better results than independent consideration of either DEED/PBDEED or DR [7] as it introduces optimality at both the supply and demand side of the power system [8]. However, solving the GTDR-DEED and GTDR-PBDEED problem only determines open loop control solutions when viewed from a control systems perspective. The disadvantage of this is that the model cannot compensate for inaccuracies and disturbances arising from modelling uncertainties. This is due to the fact that there is no way for the inaccurate system solutions to be fed back to the system and updated to obtain accurate solutions.

Closed-loop systems on the other hand are inherently able to give feedback to the optimization model [5] and update solutions [9]. Due to the superiority of closed-loop systems over open loop systems, MPC which is a prominent closed-loop approach is used in this work. MPC has found wide applications in a number of engineering applications and has recently been used in power system applications like in Ref. [10] where MPC was applied to generator maintenance scheduling [5], where MPC was applied to economic dispatch problems [11], where MPC was applied to a solar, wind, diesel battery hybrid power system. A complete introduction to MPC is provided in Ref. [12].

In view of the successful application of the MPC strategy in power system applications and its ability to handle disturbances and uncertainties, MPC is used in this work to also solve the GTDR-DEED and GTDR-PBDEED mathematical problems. MPC is utilized because in practical applications of GTDR-DEED and GTDR-PBDEED, there might be variations in system parameters like load demand or the price of energy. This can introduce a whole lot of uncertainty or disturbance in the system. MPC overcomes the aforementioned problems. The proposed MPC approach is shown to handle uncertainties and disturbance well and exhibit convergence and robustness which further makes it extremely suitable for real time and practical applications.

This paper is an extension of [8] where the GTDR-DEED model was presented. One of the additions in this work is the development of a GTDR-PBDEED model. The GTDR-PBDEED problem shows a practical framework for the integration of an incentive based demand response program with economic dispatch in a deregulated environment where one of the objectives is to maximize profit. Another addition is the application of the MPC strategy in solving both GTDR-DEED and GTDR-PBDEED. It is shown that the MPC strategy handles uncertainty and disturbance better than open loop approaches.

The rest of this paper is organized as follows: Section 2 presents a literature review of DEED, PBDEED, DR and MPC. Section 3 gives the DEED and PBDEED formulations. Section 4 introduces the Game Theory based Demand Response Program formulation. Section 5 details both the GTDR-DEED and GTDR-PBDEED mathematical models and the proposed MPC formulations applied to both models. Section 6 focuses on numerical simulations using the developed mathematical models and presents obtained results. The paper is concluded in Section 7.