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Dynamic Monitoring and Decision Systems (DYMONDS) Framework for Reliable and Efficient Congestion Management in Smart Distribution Grids

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Abstract

This paper concerns transforming today's operations and asset management in large-scale distribution grids into efficient and reliable grid management. Particular emphasis is on dynamic monitoring and decision systems (DYMONDS) embedded into system users, distribution network and operators of distribution, sub-transmission and transmission systems, all interacting to enable electricity services within the customers' preferences for acceptable type of service and electricity tariffs. Through these interactions it becomes possible to manage higher-voltage grid congestion by either: *i*) direct load control (demand side management-DSM) and/or *ii*) DYMONDS-enabled adaptive load management (ALM). It is described how these two approaches, which appear to be similar at first sight, differ in enabling customer choice with respect to both type of service and tariff determination. Finally, the paper proposes that there is potentially a major benefit from coordinating actions of distribution, sub-transmission and transmission system operators. Namely, by carefully exchanging the right information it becomes possible to implement load-transfer (LT) to relieve congestion in transmission- or sub-transmission grids by reconfiguring lower-voltage feeders in distribution grids to control the aggregate load seen at the higher voltage levels. We finally compare the economic aspects of DSM, LT and DYMONDS. A simple 60kV sub-transmission grid connected to a large distribution network in Portugal is used to illustrate these different options and the related costs and benefits.

I. Introduction

This paper concerns transforming today's operations and asset management in large-scale distribution grids into efficient and reliable grid management. We propose a data-driven software-enabled interactive decision-making framework in which both grid users and grid/electricity grid operators participate proactively. The concepts are applicable to systems with active electricity markets as well as to fully regulated utilities. While in systems with markets incentives and economic signals are provided interactively on-line, in regulated industry these can be used to define service tariffs that support differentiated electricity services at value. Time-of-Use (ToU) tariffs can be designed to differentiate between customers participating in grid congestion management from those not participating.

Recently, our research team has introduced a DYMONDS framework, which enables grid users with data-driven modeling, predictions, and decision-making [1]. The approach is fundamentally a divide-and-conquer approach over space and time: *i*) it internalizes temporal uncertainties and risks at the resource and user level, and interactive information exchange to support distributed optimization among groups of users; and *ii*) it performs static nonlinear optimization to account for nonlinear network constraints and enables corrective actions as new information becomes available [2]. A simulation-based proof of concept for low-cost green electric energy systems in the Azores Islands has been carried out and is reported in [3].

In this paper we introduce a possible application of this framework to managing congestion in large-scale distribution grids with data-driven on-line participation and information exchange between the utility operators and the grid users. We describe how by building on the existing software tools developed by the co-authors of this paper [3-5] small groups of grid users – photovoltaics (PVs), electric vehicles (EVs), residential loads – can be aggregated to participate in wholesale grid congestion management at value, in parallel with the forward-looking distribution grid operator performing reconfiguration and voltage control [8,9]. This is done by interfacing: *i*) DYMONDS software for creating customer preferences to participate in congestion management [2,3]; *ii*) an extended AC OPF for scheduling aggregated groups of system users within the ranges of adjustable power and within the ranges of prices the aggregate users are willing to participate at; and *iii*) DPlan software for reconfiguration during abnormal conditions needed to implement preferences of small aggregated users

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connected to the lower level distribution voltages [4]. A new method is introduced to use AC Optimal Power Flow (AC OPF) [5] and compute locational marginal prices (LMPs) to be sent to the aggregated groups of grid users referred to here as Distribution-Smart Balancing Authorities (D-SBAs) to participate in reducing congestion in the higher level network operated by the sub-transmission or the transmission operator.

One of the major difficulties with implementing and testing DYMONDS for efficient scheduling during normal operations is a striking lack of data about topology and asset characterization to the level of detail necessary. Moreover, it should be quite clear that it is practically impossible to perform reconfigurations to implement differentiated reliability of service during abnormal conditions without relying on D-SBA aggregation. Given the overwhelming complexity of the reconfiguration problem [10] we propose to introduce multi-level DYMONDS -DPlan supported reconfiguration method. D-SBA level reconfiguration is done by zooming into the detail of lower voltage grid portions, such as neighborhoods.

In this paper we consider several qualitatively different ways for managing higher-voltage-level congestion. In Section II we describe an approach to congestion management, by means of: *i*) load transfer (LT); *ii*) direct load control and, *iii*) DYMONDS-enabled adaptive load management (ALM). In Section III, a conventional DSM is described which is typically used to eliminate reliability problems, such as line congestion on a pre-agreed basis with the system operator. The problem of DSM for managing congestion is formulated as an optimization problem and the results are illustrated using a 60kV sub-transmission system. In Section IV a mathematical formulation in support of load transfer approach is described, and the approach is illustrated using the same 60kV network. In Section V a DYMONDS-enabled adaptive load management is introduced as yet another means of managing congestion. This approach is posed mathematically and illustrated on the same 60kV sub-transmission grid. A discussion and comparison of three proposed alternative methods for managing congestion in sub-transmission and/or transmission grids is provided and the implications on possible ToU tariffs are described. In Section VI we close with preliminary conclusions and open questions for future research.

II. DYMONDS-enabled Approach to Congestion Management

We start by considering a typical large distribution network connected to a sub-transmission 60kV grid shown in Figure 1. It can be seen in this figure that a very large number of small, typically residential and small commercial users are connected to the 60kV substations marked as yellow circles.

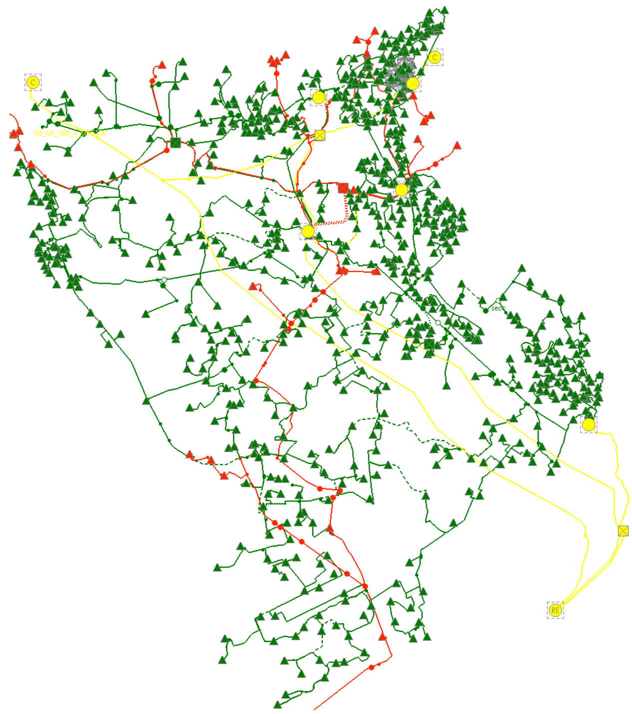

Figure 1 – Multi-level geographical network representation (sub-transmission at 60kV in yellow, and distribution at 30kV in red and 15kV in green).

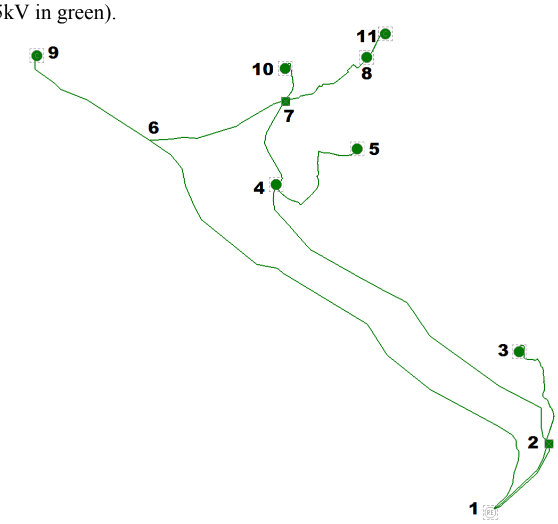

Figure 2 – Sub-transmission 60kV geographical network representation with current filter enabled (green means currents are below cable rating)

Shown in Figure 2 is the 60kV sub-transmission network only. During normal operating conditions when all 60kV lines are in service there is no congestion, namely power can be delivered to all 60kV substations so that the peak load at all substations shown in TABLE I is supplied. The main power source is bus 1 in Figure 2, which is supplied through the wholesale electricity market of Portugal. The load is taken for May 14th and the corresponding price of electricity for that day obtained from the wholesale market is shown in Table II.

TABLE I – PEAK LOAD CHARACTERIZATION

Bus ID	P [MW]	Q [Mvar]
1	0	0
2	0	0
3	18.429	5.593
4	1.900	0.442
5	20.300	6.472
6	0	0
7	0	0
8	18.433	7.963
9	7.000	2.000
10	20.338	6.309
11	7.000	2.000

TABLE II – MARKET PRICES ON MAY 14TH

Hour	Price [€/MWh]	Hour	Price [€/MWh]
1	50.07	13	58.51
2	48.00	14	57.50
3	45.73	15	51.30
4	45.12	16	50.00
5	45.73	17	44.56
6	48.00	18	38.40
7	50.20	19	36.86
8	54.20	20	38.95
9	57.24	21	44.22
10	60.13	22	48.78
11	60.98	23	47.50
12	58.51	24	36.05

Small electricity users in Portugal have typical ToU tariffs that reflect bundled cost of energy and delivery. Delivery cost reflects transmission-, sub-transmission- and distribution-grid cost. The delivery cost part of ToU tariffs has historically been distributed to different classes of customers, and has not been designed to explicitly reflect the effects of system users on congestion. In Portugal even large industrial users connected to the 60kV sub-transmission and higher-voltage levels are not given so-called locational marginal prices (LMPs), which could be used as economic signals to adjust consumption when congestion occurs. In portions of the US electric power systems with active electricity markets the transmission level (and even sub-transmission level) users are given LMP signals and could participate in congestion management and are compensated for this participation. The small residential customers still have fixed tariffs, often not even ToU differentiated.

Clearly, both technical and economic signals for congestion management need re-thinking. The electricity tariffs to small users are fixed and are often hard to relate to the ever-changing wholesale electricity markets. Viewed from the sub-transmission and transmission levels, the aggregate effect of many small residential users, on one hand, and larger industrial loads connected to 60kV, for example, should be the same. It is with this observation in mind that this paper is written. Utilities are beginning to rely on DSM, which is a direct load control of pre-agreed type of interruptions with customers at the time the rate is set. Traditional DSM suffers from two major problems: *i*) it does not interrupt the service according to customer's preferences; and, *ii*) the retail rates are not sufficiently granular to differentiate among customers capable of participating in DSM and those not doing it. In what follows, we consider several different approaches to give more explicit incentives to the end users to participate in system management at value.

2.1 Reconfiguration of distribution system users into D-SBAs for congestion management

Given the complexity created by the sheer number and diversity of distribution grid users in real-world grids, it becomes necessary to aggregate these users into D-SBAs that would communicate their aggregate willingness to participate in higher voltage network congestion. D-SBA level aggregation makes data-driven cooperation for creating energy portfolios within the members of a D-SBA manageable; as an example, PVs could cooperate with EVs geographically connected inside a D-SBA. The utility operators can use the same SBAs for detailed reconfiguration of grid equipment both to manage congestion inside an SBA and to reconfigure switches inside the D-SBA. D-SBAs become a basic means of communicating with HV grid operators and the wholesale electricity market; each SBA has one locational marginal price (LMP) as seen by the wholesale market. This LMP gives incentives to the small users to participate in congestion management at value determined by the D-SBAs. It is possible to think of these D-SBAs as the load serving entities (LSEs). Utilities are today D-SBAs, by default. The qualitative change in the proposed SBA-based approach is that the SBAs are formed in a bottom-up approach through bilateral message passing about their needs and characteristics. D-SBAs form as a result of message passing-supported cooperative games for congestion management in response to the LMP signals given by the wholesale markets/HV grid operators.

2.2 DYMONDS-DPlan Interactive Exchange between the SBAs and the Grid Operators/Markets for Congestion Management

The information exchange between the D-SBAs and grid operators/wholesale markets is analogous to the one proposed in DYMONDS [1-3]. The D-SBAs and the grid itself further generalize to utilize data-driven learning. The major benefit comes from the spatial management of highly complex distribution grids by adaptive forming of D-SBAs. We illustrate why this is an essential part for operating high penetration of very small users seen as highly stochastic by the grid operators. A DYMONDS-DPlan software will be described to show smart unique functionalities of small users within the complex distribution systems. The example used in the paper will show DPlan simulated mitigation of overloads/congestion in the higher voltage levels by reconfiguring at the lower levels by the SBAs. This example will illustrate that boundaries for network management cannot be established strictly based on voltage levels, even when the lower voltage network is radial. The medium-voltage (MV) and low-voltage (LV) grids are reconfigurable and the flexibility induced by their reconfiguration should be accounted for in managing higher-level loads. This functionality could complement price-responsive demand for congestion management during normal operation. The spatial and temporal boundaries become liquid and much data management combined with the physics-based modeling and optimization must be carefully combined to best utilize various assets during highly variable conditions.

2.3 System-Level AC Optimal Power Flow for Coordinating D-SBAs

During normal operation the D-SBAs provide their demand and supply functions. At the same time, the grid operator will use AC OPF software to coordinate critical voltage settings at the high-voltage (HV) grid level (power plants, settings of large FACTS (Flexible AC Transmission System) devices, on-load tap changing transformers, etc). To illustrate the effects of system-wide coordinated voltage optimization we will use an existing deterministic AC OPF owned by the first author's start-up company, New Electricity Transmission Software Solutions (NETSS, Inc) that has been tested on very large-scale systems [5].

In summary, this paper proposes that it is necessary to integrate a data-driven approach to grid management by both grid users and the grid operator. Using simulations of a real-world distribution grid we illustrate how an interactive combination of decision-making tools by the grid users (DYMONDS), a distribution grid management tool (DPlan) and a robust AC OPF jointly enable much more efficient and reliable congestion management in large-scale distribution grids than today.

III. Direct Load Control for Congestion Management

Generator re-dispatch is typically used to solve line congestion in today's network operations. Re-dispatch comes with the cost of a less efficient (sub-optimal) solution, and this cost is passed onto the customers through higher energy prices.

Demand participation has been envisaged solely as an additional control over the magnitude of nodal demand to be enabled by a pool of consumers/producers with the willingness to participate in the demand side management (DSM). This means that demand is considered as flexible in time for each network node.

As in generation re-dispatch, here we formulate DSM as an optimization problem where the objective function is the sum of the demand reduction costs in order to relieve the congestion in the network. Constraints include the power flow equations as well as the demand reduction constraints. In the following, we describe our formulation to such problem:

$$
\begin{aligned}
\min \quad & \sum_{i=1}^{N} C\left(\Delta D_i\right) \\
\text{s.t.} \quad & S_i = G_i - D_i,\ (i = 1,\cdots,N) \\
& D_i = D_i^0 - \Delta D_i \\
& S_i^* = V_i^* \sum_{j=1}^{N} V_j Y_{ij} \\
& 0 \le \left|I_{ij}\right| \le \left|I_{ij\max}\right|,\ \ (i = 1,\cdots,N;\ j = 1,\cdots,N) \\
& 0 \le \Delta D_i \le \Delta D_{i\max}
\end{aligned}
$$

where,
ΔD_i is the demand variation at node i;
$C(\Delta D_i)$ is the demand variation cost at node i;
S_i is the total injected power into node i;
G_i is the total generation at node i;
D_i is the total demand at node i;
V_i is the complex voltage at node i;
Y_{ij} is the element ij of the admittance matrix;
I_{ij} is the current flow between node i and node j.

To illustrate the DSM solution approach to congestion management, we present the results obtained for two case studies. The first case is the one caused by the loss of the line between buses 1 and 6, and the second case is the one caused by the loss of the line between buses 2 and 4 (see Figure 2).

For simplicity, we consider that only two HV loads are willing to participate in the DSM program (bus 9 and bus 11). We assume that loads are willing to reduce their demand by 20% given electricity price $p1$, by more 20% for given $p2$ and for another 20% given price $p3$, where $p1 < p2 < p3$ with prices $p1$, $p2$ and $p3$ in \$/MWh. Optimal DSM solved the congestion problems in both cases. Results are shown below:

TABLE III – CASE 1 OPTIMAL DSM RESULTS

	BEFORE	AFTER

Bus ID	BEFORE		AFTER	
	P [MW]	Q [Mvar]	P [MW]	Q [Mvar]
9	7	2	4.190	1.972
11	7	2	4.092	1.169

TABLE IV – CASE 2 OPTIMAL DSM RESULTS

Bus ID	BEFORE		AFTER	
	P [MW]	Q [Mvar]	P [MW]	Q [Mvar]
9	7	2	4.154	1.187
11	7	2	2.800	0.800

From the results obtained for the two case studies it is seen that the solution for the second case can also be used to solve the first case. Using *p*1 equal to 35$/MWh, *p*2 equal to 50$/MWh and *p*3 equal to 75$/MWh the solution to case 1 has a total cost, associated with DSM of 247$/h and for the second case the total cost of 347$/h. The solution can be more efficient if we expand the DSM approach to a larger number of loads/clients willing to reduce their demand, turning off or delaying the use of some appliances like water heating, air conditioners or washing machines.

IV. Load Transfer Approach to Congestion Management

Load transfer (LT) approach can be used as a complementary approach to relieve congestion for the scenario when the total load served by the 60kV network must remain the same, i.e., no DSM. In a system with multiple voltage levels, the transfer of load at the higher level can be enabled by the lower-voltage network, which can be reconfigured to transfer load between adjacent higher-voltage nodes [8, 9]. This type of control does not change the total load served but only the way it is distributed by the higher-voltage network nodes. LT enables flexibility with respect to the place in the higher voltage network, as illustrated in Figure 3.

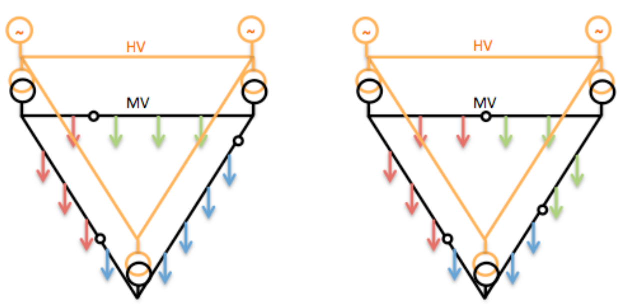

Figure 3 – Load Transfer example. Original load in LHS figure: 4 units to red bus; 3 units to green bus; and 5 units to blue bus. Reallocated load in RHS figure: 5 units for red bus; 4 units to green bus; and 3 units to blue bus.

Efficient LT requires close-to-real-time state estimation of the MV network. Minimal information for robust state estimation requires measurements of currents in the MV feeders and currents in the normally closed switches. Feeder measurements are currently available in most SCADA systems; switches measurements can today be obtained at a reasonable cost.

Communications must be designed to make the information available in the control room, and algorithms must be developed to optimize load LT according to the particular objective of congestion management. LT can be formulated as an optimization problem. In the following, we describe our formulation to such a problem as:

$$\min \sum_{i=1}^{N}\sum_{j=1}^{N} C\left(D_{ij}\right)$$

$$\text{s.t.}\quad S_i = G_i - D_i,\ (i = 1,\cdots,N)$$

$$S_i^* = V_i^* \sum_{j=1}^{N} V_j Y_{ij}$$

$$D_i = D_i^0 - \sum_{j=1}^{N} D_{ij}$$

$$0 \le \left|I_{ij}\right| \le \left|I_{ij\,\max}\right|,\ (i = 1,\cdots,N;\ j = 1,\cdots,N)$$

$$0 \le D_{ij} \le D_{ij\,\max}$$

where,
D_{ij} is the load transferred between node *i* and node *j*;
$C(D_{ij})$ is the cost of load transferred between node *i* and node *j*;
S_i is the total injected power into node *i*;
G_i is the total generation at node *i*;
D_i is the total demand at node *i*;
V_i is the complex voltage at node *i*;
Y_{ij} is the element *ij* of the admittance matrix;
I_{ij} is the current flow between node *i* and node *j*.

To illustrate the LT solution approach to congestion management, we present the results obtained for the two case studies described in the previous section. The MV network topology is such that only allows significant transfer between three HV substations (bus 3, 5 and 10). Load transfer capabilities and the corresponding number of switching operations are given in the tables below.

As we will see next, like DSM also LT alone can be used to solve congestions problems since both case studies can be solved. And again, the LT solution for the second case also solves the first case. For the results presented next we assume that the load transfer between buses is a continuous variable, which in reality is not: MV loads are lumped not continuously distributed and switches are limited in number. So, the effective transfer amount must be estimated based on switch locations in the MV network, which reinforces the need to have real time and accurate measurements in the different voltage levels.

The data presented in Tables V and VI was extracted from DPlan using the MV network reconfiguration capabilities to transfer load between HV network nodes.

TABLE V – LOAD TRANSFER CAPACITY (IN MW)

From/To	3	5	10
3	-	1.85	5.85
5	4.47	-	2.95
10	2.75	5.68	-

TABLE VI – NUMBER OF SWITCHING ACTIONS FOR MAXIMUM TRANSFER

From/To	3	5	10
3	-	2	2
5	4	-	4
10	2	6	-

Optimal LT solved the congestion problems in both cases. Results are shown below:

TABLE VII– CASE 1 OPTIMAL LT RESULTS

Bus ID	BEFORE		AFTER	
	P [MW]	Q [Mvar]	P [MW]	Q [Mvar]
3	18.429	5.593	24.136	7.325
5	20.300	6.472	17.343	5.529
10	20.338	6.309	17.588	5.456

TABLE VIII – CASE 1 RESULTS ON TRANSFERRED LOAD

From/To	3	5	10
3	-	0	0
5	2.957	-	0
10	2.75	0	-

TABLE IX– CASE 2 OPTIMAL LT RESULTS

Bus ID	BEFORE		AFTER	
	P [MW]	Q [Mvar]	P [MW]	Q [Mvar]
3	18.429	5.593	25.359	7.696
5	20.300	6.472	16.120	5.139
10	20.338	6.309	17.588	5.456

TABLE X – CASE 2 RESULTS ON TRANSFERRED LOAD

From/To	3	5	10
3	-	0	0
5	4.18	-	0
10	2.75	0	-

Note that these results were obtained for the *optimal solution*. Nevertheless, the maximum transfer capability between buses 5-3 and 10-3 solves both problems with only 6 switching operations. Considering that a switching operation comprises two switching actions (close a normally-open switch and open a normally-close switch), and taking a switch cost of 50$ the LT solution would be cheaper that the DSM solution if the congestion would last for one hour.

In order to compare both approaches (DSM and LT) performance in solving one-hour duration congestion we classify the optimal solution depending on the LT and DMS prices. The price relations for DMS are $p2 = 1.4286p1$ (1.4286 = 50/35) and $p3 = 2.1429p1$ (2.1429 = 75/35).

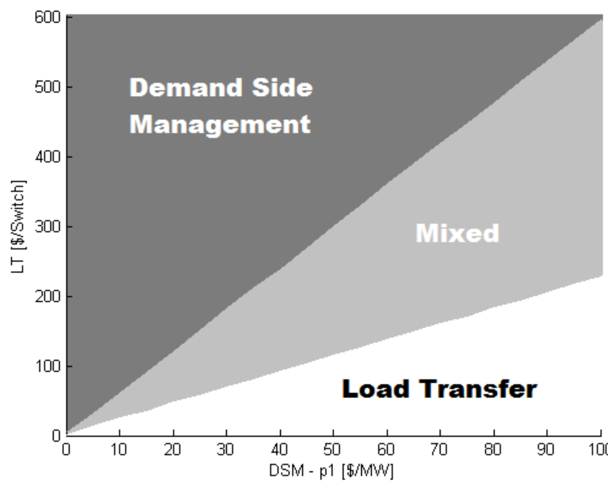

Figure 4 – Optimal solution to solve the 1h congestion vs prices. For the range of prices represented in white, the optimal approach is to use LT alone, for the light grey, the optimal is a mixed of LT and DSM, and for the dark grey, the optimal is DSM alone.

V. DYMONDS-based Approach to Adaptive Load Management (ALM)

In this section a DYMONDS-enabled adaptive load management is introduced as yet another means of managing congestion. This approach is posed mathematically and illustrated on the same 60kV sub-transmission grid. Adaptive Load Management (ALM) is a comprehensive demand response framework that accounts for preferences of the individual end-users at the value of consuming power defined by the users themselves [6, 7]. The basic information exchange in DYMONDS is shown in Figure 5 [11, 12]. Basically, all system users i, generators and/or responsive demand, prepares their supply cost and benefit functions $C_i(P_{Gi}(k))$ and $B_i(L_i(k))$, and the power limits within which they wish to be scheduled, respectively, for all hours k in the next day based on the likely LMP(k) provided by the system operator. The system operator then performs social welfare maximization (the same as total generation and demand cost minimization) subject to generation and demand power limits defined by the system users. The look-ahead decision making by each system user i is done to compute the cost functions for all hours given specific inter-temporal constraints unique to each user. This is done using LMPs for all hours k. As a result, cost functions whose parameters (cost coefficients and power limits) vary with each hour are obtained and sent to the system operator for clearing. The system operator performs static optimization for each hour for the next 24 hours and sends the cleared power quantities $P_{Gi}^*(k)$ and $L_i^*(k)$ and the actual LMPs $\lambda^*(k)$, respectively. There exist several variations of sequential clearing, optimization problems 2 and 3 denoted in Figure 5, can be found in [11, 12]. Note that if the same price of electricity, or electricity tariff, is given to all users, independent of their effects on congestion, the cleared quantities do not help with congestion. In this paper we describe next how an AC Optimal Power Flow (AC OPF) is used to compute LMPs that provide different signals to the users at different locations in the grid to adjust and help with congestion management.

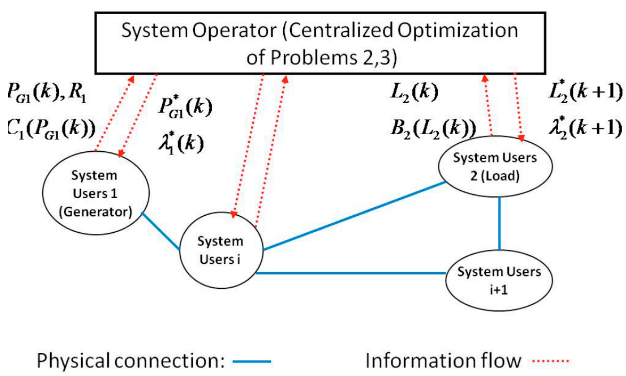

Figure 5 – DYMONDS information exchange between system operator and system users [10]

In what follows DYMONDS information exchange is applied to provide incentives to the price responsive adjustable demand to manage congestion in the 60kV sub-transmission network shown in Figure 2 during the same two line outage scenarios used for introducing DSM and LF above. In this network the only generator is the power provided by the electricity market at bus 1, and the hourly electricity prices are taken from the energy market shown in TABLE II above. The cost demand functions are obtained by the elastic demand maximizing its own benefit for the day ahead given these prices (demand is modeled as negative generation with varying limits). These demand functions are then cleared using an AC OPF subject to power flow constraints during normal conditions in the 60kV network, as well as during the lien outage connecting buses 1 and 6, and buses 2 and 4, respectively. It is described next how this process enables the responsive demand to help with congestion management during the outages and be rewarded for according to the LMPs.

5.1 Decision making by the responsive demand

In this paper we used the *functional clearing* method described in order to calculate the demand functions [7]. The price sensitivity of demand is calculated at every hour based on the optimization problem of each end-user, and the entire system is cleared with the demand functions including the price sensitivity of demand at each bus and for given generation supply functions. While in the direct load control methods the system operator assumes certain costs for load curtailment and reinforces it whenever the system operator sees as needed for the system, ALM acquires the cost/benefit of curtailing/using electric energy from the end-users bottom up. Demand functions that include the information of the end-users' benefit of consuming electricity are then sent to the system operator so that demand is cleared with the rest of supply functions in the system.

In our example of air conditioner loads, the optimization problem that an end-user solves is:

$$\begin{aligned} \min_{x,d} \quad & \lambda^T d + (x - x_{\text{set}})^T W_T (x - x_{\text{set}}) \\ \text{s.t.} \quad & x(k+1) = \varepsilon x(k) + (1-\varepsilon)(d(k) + \gamma\theta(k)) \forall k \\ & d_{\min} \le d \le d_{\max} \\ & x_{\min} \le x \le x_{\max} \end{aligned}$$

where λ, d and x are the expected price, demand quantity, and the indoor temperature over the optimization time horizon, respectively. x_{set} and W_T denote the temperature setpoints and the weights between the temperature setpoints at different time steps, and ε, γ, θ are the parameters relevant to the indoor temperature dynamics with respect to the electricity usage [6]. By solving the optimal demand d with respect to the expected set of prices λ and by calculating different sets of optimal demand with respect to slightly perturbed values from the expected prices, we obtain the estimate of the price sensitivity of demand.

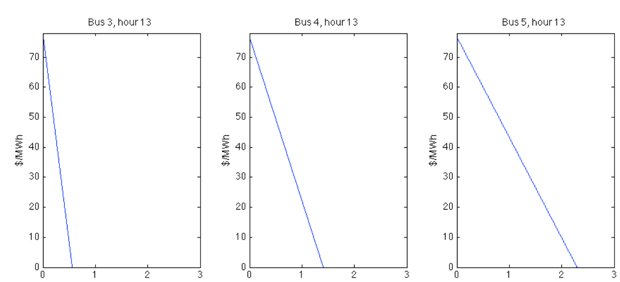

Figure 6 – Demand functions at buses 3, 4, and 5 at hour 13

From Figure 2, three buses are assumed to have flexible loads: buses 3, 4, and 5, since these were the buses that had the least "flat" daily load curves. The price data is taken from the day-ahead market in Portugal on May 14th, 2013 shown in TABLE II. The weather temperature was assumed to be 10 degrees Celsius higher than the actual data in order to simulate the air conditioning consumption. A total of 200, 500, and 800 buildings were simulated for the buses 3, 4, and 5, respectively. The power ratings of the individual air conditioners range from about 5 to 20 kW. A sample set of demand functions are shown in Figure 6.

5.2 AC OPF clearing for clearing 60kV market using DYMONDS-based responsive demand bids

To illustrate the effects of DYMONDS-based congestion management, we consider three different hours: Hour 1, 13, and 24. These hours are qualitatively different as it can be seen from Figure 7 depicting daily load profiles at nodes 3, 4, and 5.

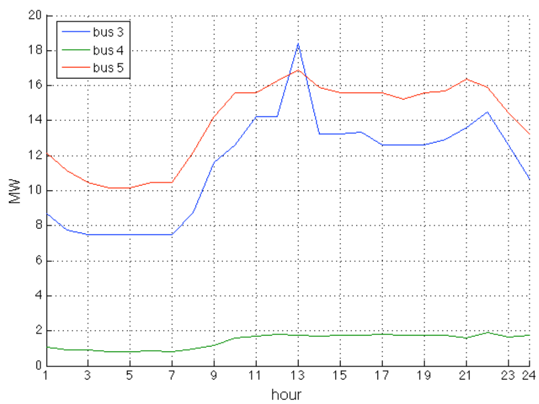

Figure 7—Hourly total load change at buses 3, 4, and 5

The peak load occurs at hour 13 and hour 24 is an hour in which loads are inelastic. Hour 1 is an otherwise typical normal load hour with some elasticity as shown in Figure 6 above.

Shown in TABLES XI, XII and XIII are the results of using AC OPF to account for responsive demand at buses 3, 4 and 5 for normal topology, line outage 1-6 and line outage 2-4, respectively. These tables present adjusted generation at bus 1, and reduced demand at buses 3, 4 and 5, which are price-responsive. The demand functions are created assuming the electricity market price given in TABLE II as well as assuming that the price of electricity is the one of a typical coal plant. It can be seen that there is no active congestion, i.e., the optimization sensitivity with respect to the flows (OSFs) are zero, except at the peak hour 13. It is interesting to observe that it is these additional cost increases due to OSFs that directly contribute to the increased LMPs during hour 13. It is this signal that gives incentive to the adjustable loads to respond and enable delivery within the line flow limits.

TABLE XI – THE RESULTS OF AC OPF SCHEDULING OF DYMONDS FOR NORMAL TOPOLOGY

Hour	Cost ($)	Fixed (MW)	Generation (MW)		LMPs ($/MWh)		OSF ($/MWh)
1	-397	57	1	76	1	50	none
			3	-9	3	50	
			4	-2	4	51	
			5	-6	5	51	
13	1936 (market price)	88	1	10	1	58	none
			3	-9	3	58	
			4	-2	4	60	
			5	-6	5	60	
	-2477 (coal price)	88	1	107	1	19	none
			3	-9	3	19	
			4	-2	4	19	
			5	-6	5	19	
24	2558 (market price)	70	1	71	1	36	none
			3	0	3	36	
			4	0	4	36	
			5	0	5	36	
	1212 (coal price)	70	1	71	1	18	none
			3	0	3	18	
			4	0	4	18	
			5	0	5	18	

TABLE XII – THE RESULTS OF AC OPF SCHEDULING OF DYMONDS FOR LINE OUTAGE 1-6

Hour	Cost ($)	Fixed (MW)	Generation (MW)		LMPs ($/MWh)		OSF (2-4) ($/MWh)
1	-394	57	1	76	1	50	none
			3	-9	3	50	
			4	-2	4	51	
			5	-6	5	51	
13	3380 (market price)	88	1	101	1	58	-208
			3	-9	3	58	
			4	-1	4	279	
			5	0	5	280	
	-782 (coal price)	88	1	101	1	19	-247
			3	-9	3	19	
			4	-1	4	279	
			5	0	5	279	
24	2582 (market price)	70	1	71	1	36	0
			3	0	3	36	
			4	0	4	37	
			5	0	5	37	
	1224 (coal price)	70	1	71	1	18	0
			3	0	3	18	
			4	0	4	18	
			5	0	5	18	

TABLE XIII – THE RESULTS OF AC OPF SCHEDULING OF DYMONDS FOR LINE OUTAGE 2-4

Hour	Cost ($)	Fixed (MW)	Generation (MW)		LMPs ($/MWh)		OSF (1-6) ($/MWh)
1	-326	57	1	76	1	50	none
			3	-9	3	50	
			4	-2	4	53	
			5	-6	5	53	
13	3550 (market price)	88	1	101	1	58	-52
			3	-9	3	58	
			4	0	4	118	
			5	0	5	11	

						9	
	-600 (coal price)	88	1	107	1	19	-92
			3	-9	3	19	
			4	-2	4	11 8	
			5	-6	5	11 9	
24	2602 (market price)	70	1	71	1	36	0
			3	0	3	36	
			4	0	4	38	
			5	0	5	38	
	1234 (coal price)	70	1	71	1	18	0
			3	0	3	18	
			4	0	4	19	
			5	0	5	19	

TABLE XIV – DEPENDENCE OF FINANCIAL OUTCOMES ON CONGESTION CHARGES FOR HOUR 13

	Generator cost ($)	Generator revenue ($)	Fixed load charge ($)	Marginal surplus ($)
Normal; market price	1936	5225	5296	71
Normal; coal price	-2477	1710	1736	25
1-6 line out; market price	3448	5112	12688	7575
1-6 line out; coal price	-782	1332	20381	19049
2-4 line out; market price	3556	5275	9368	4092
2-4 line out; coal price	-598	1648	8695	7047

VI. Preliminary Conclusions and Future Work

In this paper we have for the first time put forward the premise that aggregate loads in lower voltage distribution systems can be used for congestion management in sub-transmission and transmission grids. It is shown that congestion management can be implemented in three different ways, using direct load control (DSM), load transfer (LT) and DYMONDS-enabled demand response to LMPs. The last approach allows for customer valuation of both locational and temporal electricity service, and could be used as the information when the system operator schedules resources. Adaptive load management is one possible implementation, and it is shown that it has a potential to manage congestion during severe line outages in sub-transmission and transmission network. For this to happen, it is essential to give incentives to the users to adjust. It is shown how congestion affects generation cost (adaptive demand is referred to as generation here), generation revenue, total fixed load charge and congestion cost measured in terms of network marginal surplus. The next steps are to test this concept on large-scale systems with typical distribution loads. The study in this paper shows that there are significant benefits from doing this. Another major open question is the design of longer-term ToU tariffs to incentivize longer-term commitment by the users to participate in congestion management. If such commitments are made, responsive customers will be paid for reduced capital cost investments in transmission wires, otherwise necessary. Adapting these tariffs is a major next challenge.

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