ELECTRICAL LOAD FORECASTS IN LONG –TERM AND IMPACT ON LOAD MANAGEMENT APPLICATION

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ABSTRACT

The target of this paper is impacting Demand Side Management (DSM) when it is applied at different sectors; residential, commercial, public, government, agriculture, industrial and the total load of these sectors on national network of power system in Egypt for year (2009-2010) and estimating load forecast for these sectors by Adaptive Network Fuzzy Inference System (ANFIS) techniques during the period from year (2010-2011) to year (2020-2021).The daily load curve for maximum load of August month for year (2009-2010) as base year on Egyptian power system is expressed. Daily load forecast by using three techniques; Adaptive Network Fuzzy Inference System (ANFIS) technique, Artificial Neural Network (ANN) technique and Regression technique are estimated during period from year (2010-2011) to year (2020-2021). he is found the ANFIS technique is more suitable than other techniques. The daily load curve for maximum load of day from year (2009-2010) as base year on Egyptian power system is presented. Estimated daily load forecast by (ANFIS) technique during period from year (2010-2011) to year (2020-2021)is shown.

INTRODUCTION

Using the forecasting of hourly load curve for maximum load of the year and maximum load forecasting of hourly load curve for August month for year is estimated during the period from year (2009-2010) to year (2020-2021) by applying ANFIS technique [5,6].
Impact of DSM by clipping load or load shifting is shown for different sectors of the customers; such as residential, commercial, public, government, agriculture, industrial and total load for these sectors on these hourly load curves during the same period [1,2,3]. Economic evaluation of load management applications by estimated saved energy, saved fuel and financial saving and the avoided capacity cost, avoided energy cost and total cost of Egyptian network during the same period [4], which affects the output of the node. These networks are learning a relationship between inputs and outputs.

ADAPTIVE NETWORK FUZZY INFERENCE SYSTEMS (ANFIS)

Fuzzy systems present particular problems to a developer ANFIS is an adaptive network that consist of nodes and directional links. Associated with the network is a learning rule- for example back propagation. It is called adaptive because some or all, of the nodes have parameters which affect the output of the node. These networks are learning a relationship between inputs and outputs. Adaptive networks covers a number of different approaches but for our purposes we will investigate in some detail the method proposed by Jang known as ANFIS. The fuzzy inference system has been composed of five components: Fuzzification, knowledge base (rules), inference engine, aggregations and defuzzification Input layer Fuzzified Rule Defuzzified Output layer

DSM PROGRAMS

There are five broad strategies of load shape objectives these can be distinguished; has peak clipping, valley filling, load shifting, energy conservation and load building.

MATHEMATICAL FORMULATION OF DSM TECHNIQUES

The mathematical formulation of the DSM techniques as an optimization problem is given. Two sorts for the objective function are contributed, either to maximize the system load factor for the utility, or to minimize the total cost of the bill for the customer. While there exist two sorts for the objective function for the five DSM techniques, the imposed constraints on the demand type at different time intervals (control variables) differ from a technique to another and depend, also, on the load peculiarities and the power system. DSM programs seek to optimize either of the following two objective functions [7].

$$Max.L.F. = \left[\left[\sum_{i=1}^{N}\sum_{j=1}^{J} P_{(i,j)} \times t_{(j)}\right] / \sum_{j=1}^{J} t_{(j)}\right] / \sum_{i=1}^{N} P_{(i,k)}$$

$$Max.L.F. = \left[\left[\sum_{j=1}^{J} P_{TO(j)} \times t_{(j)}\right] / \sum_{j=1}^{J} t_{(j)}\right] / P_{TO(K)}$$

$$Min.C = \left[\sum_{i=1}^{N}\sum_{j=1}^{J} P_{(i,j)} \times t_{(j)} \times ce_{(i,j)}\right] + \left[\sum_{i=1}^{N}\sum_{j=1}^{J} P_{(i,j)} \times cd_{(i,j)}\right]$$

Where,
L.F.: is the system load factor.
$P_{(i,j))}$:is the demand of load type i at time interval numberj.
N: is the total number of load demand types.
J : is the total number of time intervals.

$P_{TO(j)}$: is the total demand for all the loads types from j=1 to j=J over the time interval number j.
k : is the number of time interval at which the maximum demand for all the load types numbers from i=1, N over all the time duration from j=1, J occurs.
C: is the total cost of the electrical demand and energy consumption.
$ce_{(i,j)}$: is the cost of energy for load type i at time interval number j.
$cd_{(i,j)}$:is the cost of demand for load type i at time interval number j.

RESULTS

Energy demand forecast (GWh) for residential, commercial and public sector by using ANFIS technique from year (2009-2010) to year (2020-2021) as shown Table (1).

TABLE I
ENERGY DEMAND FORECAST (GWH) FOR RESIDENTIAL, COMMERCIAL AND PUBLIC SECTOR BY USING ANFIS TECHNIQUE FROM YEAR (2009-2010) TO YEAR (2020-2021)

Year	Residential	Commercial	Pubic
9-10	45384	8450	12199
10-11	47660	9605	12483
11-12	50170	10336	12781
12-13	52790	11105	13023
13-14	55530	11913	13212
14-15	58380	12758	13369
15-16	61360	13639	13516
16-17	64470	14556	13670
17-18	67710	15508	13847
17-18	71090	16497	14056
18-19	74620	17524	14303
19-20	78310	18591	14591
20-21	45384	8450	12199

TABLE II
ENERGY DEMAND FORECAST (GWH) FOR GOVERNMENT, AGRICULTURE, INDUSTRIAL AND TOTAL ENERGY DEMAND FORECAST BY ANFIS TECHNIQUE FROM YEAR (2009-2010) TO YEAR (2020-2021)

Year	Government	Agriculture	Industrial	Total energy demand
9-10	5970	4638	40563	117204
10-11	6233	4893	41084	121958
11-12	6448	5120	42450	127305
12-13	6670	5353	43867	132808
13-14	6901	5592	45337	138485
14-15	7139	5837	46860	144343
15-16	7387	6087	48443	150432
16-17	7645	6342	50085	156768
17-18	7913	6602	51789	163369
18-19	8194	6867	53562	170266
19-20	8486	7137	55405	177475
20-21	8793	7412	57326	185023

- Peak Clipping Load Technique for Different Sectors by Using Hourly load curve for Maximum load of day for year

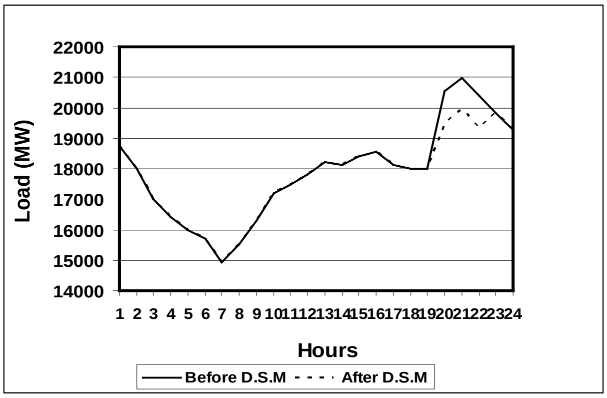

Fig. 1 shows actual load for Year (2009-2010) base year by clipping load by 1050 MW from hour 20 to hour 22

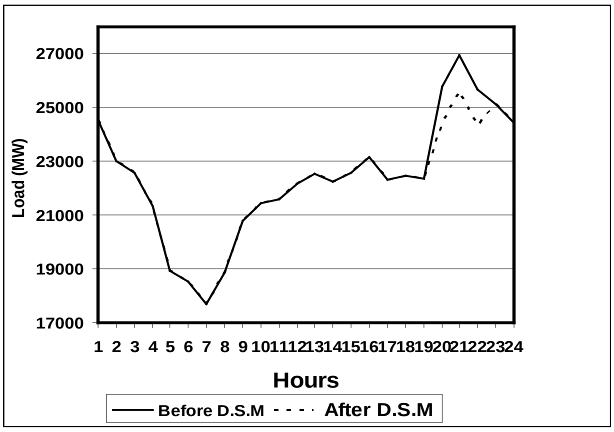

Fig. 2 Load Forecast for year (2015-2016) clipped load by 1351 MW from hour 20 to hour 22

- Load Shifting Technique for Different Sectors by Using Hourly load curve for Day of Maximum day for year

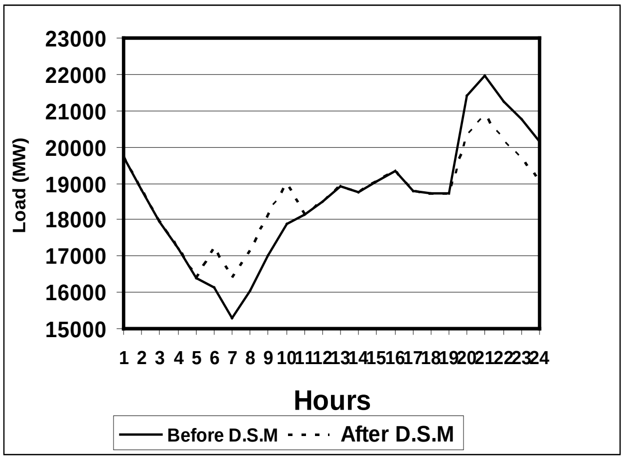

Fig.3 Load forecast for year (2010-2011) shifting load by 1095 MW from hour 20 to hour 24 to hours (6,7,8,9,10)respectively.

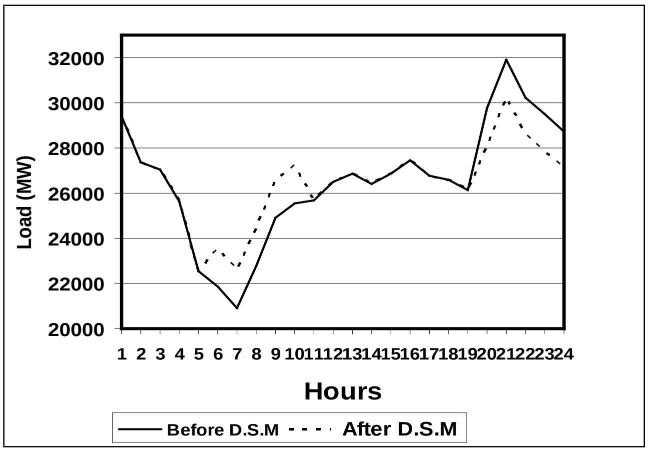

Fig.4 Load forecast for year (2020-2021) shifting load by 1672 MW from hour 20 to hour 24 to hours (6, 7, 8, 9, 10) respectively

TABLE III
FUEL CONSUMPTION AT PEAK LOAD, DIFFERENCE IN CONSUMPTION, PRICE OF MAZOUT, CAPACITY COST AND ENERGY COST DURING THE PERIOD FROM YEAR (2009-2010) TO YEAR (2020-2021)

Year	Consumption at Peak Load (Gram /KWh)	Difference in fuel Consumption (Gram/KWh	Price of Mazout (L.E)	Capacity Cost LE/KW	Energy Cost LE/KWh
9-10	300	40	205	263.42	0.126
10-11	309	41	211	268.68	0.129
11-12	318	42	217	274.045	0.131
12-13	328	43	224	279.517	0.134
13-14	338	44	230	285.099	0.137
14-15	348	45	237	290.792	0.14
15-16	358	48	245	296.65	0.142
16-17	369	49	251	302.521	0.146
17-18	380	51	258	308.561	0.149
18-19	391	52	266	314.723	0.152
19-20	403	53	274	321.007	0.155
20-21	415	55	284	327.52	0.157

TABLE IIII
AVOIDED CAPACITY COST, AVOIDED ENERGY COST AND TOTAL AVOIDED COST (MILLION LE/YEAR) DURING THE SAME

Year	Year	Avoided capacity cost (Million LE/year)due to Clipping or shifting	Avoided energy cost (Million LE/year) due to clipping load	Avoided energy cost (Million LE/year) due to shifting load	Total avoided cost (Million LE/year) due to Clipped load	Total avoided cost (Million LE/year) due to load shifting
9-10	9-10	276.591	96.579	12.571	373.170	289.162
10-11	10-11	294.205	103.116	13.830	397.321	308.035
11-12	11-12	312.411	109.317	15.211	421.728	327.622
12-13	12-13	333.743	116.797	16.791	450.540	350.534
13-14	13-14	355.233	124.612	18.410	479.846	373.643
14-15	14-15	377.739	132.758	20.227	510.497	397.965
15-16	15-16	400.774	140.428	23.260	541.202	424.034
16-17	16-17	427.462	150.598	25.373	578.060	452.835
17-18	17-18	454.510	160.218	28.297	614.729	482.808
18-19	18-19	483.415	170.435	31.019	653.849	514.434
19-20	19-20	512.969	181.309	33.974	694.278	546.943
20-21	20-21	547.613	191.628	38.130	739.241	585.744

TABLE V
ESTIMATION CLIPPED ENERGY, SAVED FUEL, FINANCIAL SAVING FUEL DUE TO CLIPPED LOAD DURING THE SAME

Year	Clipped energy (Million KWh/Year	Saved fuel (Ton/year) due to Clipped load	Financial saving of fuel (Million LE/year) due to Clipped load
9-10	766.500	229950.0	47.140
10-11	799.350	246999.1	52.117
11-12	834.480	265364.6	57.584
12-13	871.620	285891.3	64.040
13-14	909.580	307438.0	70.711
14-15	948.270	329997.9	78.210
15-16	988.932	354037.6	86.739
16-17	1031.490	380619.8	95.536
17-18	1075.290	408610.2	105.421
18-19	1121.280	438420.4	116.620

19-20	1169.736	471403.6	129.165
20-21	1220.560	511414.6	145.242

TABLE IV
ESTIMATION SHIFTING ENERGY, SAVED FUEL, FINANCIAL SAVING FUEL DUE TO LOAD SHIFTING DURING THE PERIOD FROM YEAR (2009-2010) TO YEAR (2020-2021)

Year	Shifting energy (Million KWh/Year	Saved fuel (Ton/year) due to Load shifting	Financial saving of fuel (Million LE/year) due to Load shifting
9-10	1533.000	61320.00	12.571
10-11	1598.700	65546.70	13.830
11-12	1668.960	70096.32	15.211
12-13	1743.240	74959.32	16.791
13-14	1819.160	80043.04	18.410
14-15	1896.540	85344.30	20.227
15-16	1977.864	94937.47	23.260
16-17	2062.980	101086.0	25.373
17-18	2150.580	109679.5	28.297
18-19	2242.560	116613.1	31.019
19-20	2339.472	123992.0	33.974
20-21	2441.120	134261.6	38.130

CONCLUSIONS

Estimation of the load forecast of hourly load for maximum load of day for year and maximum hourly load curve for August month for year by Adaptive Network Fuzzy Inference System ANFIS technique during the period from year (2009-2010) to year (2020-2021) are shown.
Estimation of the forecasting of energy demand by ANFIS technique and load forecast for different sectors at customer side and generate side are shown.
An implementation of the Demand Side Management (DSM) applications especially peak clipping and load shifting on different sectors for the same previous period. If reflected the estimation of the saved energy (Million KWh/year), the saved fuel (ton/year) and financial saving of fuel (Million LE/year) % Estimated also avoided capacity cost (Million LE/year) and avoided energy cost (Million LE/year) and total avoided cost (Million LE/year). DSM programs are used to advance the adoption of more efficient technologies and practices and thereby drive energy savings. DSM programs can be used to help introduce new technologies into the market place and to increase the level of adoption of these technologies to a point where new codes and standards can be implemented. If the baseline level of efficiency is substantially different from the DSM plan baseline assumption, then there may be some inconsistency between the DSM plan and the Load Forecast. This may be the case for some end uses. Where information is available and changes are practical, adjustments should be made to ensure Load Forecasting and DSM planning processes to use consistent planning assumptions regarding baseline efficiency levels. In the long term, a common planning framework and stock turnover model should be pursued.

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