DeLi2P
A User Centric, Scalable Demand Side Management Strategy for Smart Grids

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Keywords: Smart Grids, Demand Side Management, Peak Reduction, Demand Elasticity.

Abstract: Smart grids coulpled with effiicient demand side management (DSM) is an important step for greener cities of the future. DSM has the potential to significantly improve smart grid operations by reducing the peak to average ratio. Current DSM schemes are able to reduce peak load by as much as 30% which can translate to significant cost savings and reduction in green house emissions. But for realistic deployment of DSM systems in the grid there are two very important aspects which need to be considered: scalability and user acceptability. Since the current DSM algorithms are required to control potentially hundreds of thousands of devices, they have to be scalable and tractable for such myriad numbers. On the other hand DSM affects the life style of the consumer and this should be as less disruptive as possible. The various DSM techniques proposed in the literature attempt to first reduce the cost and then attempt to resolve one of the two aforementioned aspects. The result is that the techniques are either scalable or are only considerate of the deadlines of the consumers. An ideal system should cater to both of these aspects. Our system Deli2P is user centric and scalable thus catering to both of these aspects. Essentially we provide to the consumer a deadline centric interface. The deadlines solutions are generally not scalable. But instead of solving this problem as a scheduling for deadline problem we transform the problem to a priority-based problem thus making it scalable for large number of devices. Our results show that with this scheme we can reduce peak power by upto 30% but without violating consumers‘ deadlines.

1 INTRODUCTION

The continuous increase in electricity demand and the shrinking resources of energy has resulted in a scarcity of electricity. In such a scenario conserving and optimally consuming the existing resources has gained paramount importance. In fact energy efficiency is being called as ‘the most important’ fuel for the future. One of the major ways for efficient energy management is demand side management (DSM) (Gellings, 1985). Coupling DSM with the future smart grids technologies therefore is being seen as the major resource for the future smart grids (Rahimi and Ipakchi, 2010). The goal of these future DSM systems is to manage the domestic consumer’s load for a more environmental and economically efficient energy generation scheduling. This is usually achieved by offloading the electric consumption from high cost timings to other timings when the electricity price is low (Liu et al., 2014). This phenomenon is commonly known as peak shaving.

However, for a DSM strategy to be viable for domestic consumer it is imperative that this load movement is acceptable to the consumers‘ schedules and practical constraints. Historically it has been observed that strategies which do not consider consumers preferences as first class requirement fail to deliver due to stiff resistance or non-cooperation from the consumers. As Kim and Shcherbakova report on the reasons for DSM failures, the consumer needs to be involved in the DSM activities and her requirements need to be understood and catered for (Kim and Shcherbakova, 2011). To cater to the consumers‘ needs there are two strategies used by the DSM planners and researchers: Either consumer’s exact requirements are captured by eliciting the deadline within which the task must be achieved (Arif et al., 2013), or the devices are assigned priorities and these priorities are used for planning (Beal et al., 2012).

The difference in the two strategies on operational

Muhammad Ali S., Naveed M., Javed F., Arshad N. and Ikram J..
DeLi2P - A User Centric, Scalable Demand Side Management Strategy for Smart Grids.
DOI: 10.5220/0005437301480156
In *Proceedings of the 4th International Conference on Smart Cities and Green ICT Systems* (SMARTGREENS-2015), pages 148-156
ISBN: 978-989-758-105-2

level may seem insignificant initially but from a computational perspective the two strategies have significant implication in the scalability of the system. The preference based scheduling problem is a very common problem in operations research and computer science. Various job scheduling tasks exist in real world and researchers have analyzed this problem in detail. Scheduling of loads constrained by preferences is very similar to job scheduling problem. However, this problem is classified as NP-complete problem and to-date no scalable algorithm has been proposed to solve this problem. The implication of this NP-complete classification is that a problem without necessary transformations will be intractable for large number of devices thus making it not suitable for large number of devices. As the number of devices increase the algorithm will take an exponentially more time for computation.

On the other hand priority-based systems are able to aggregate the devices into priority classes and the planning decision is reduced from controlling hundreds of devices under constraints to just controlling each priority class. Since the number of priority classes is much smaller than number of devices, planning for this system is tractable. ColorPower is an example of such a technique (Ranade and Beal, 2010). This reduction in size makes the problem tractable for a micro-grid or even city level scheduling.

However, priority classes are limiting in that deadlines for individual devices are not part of the scheduling. This is problematic as this results in lower consumer satisfaction as the needs of the consumer can be violated. From the experience of Power7 of UK we know that the consumers‘ life styles are dynamic and such fixed measures are not very useful. To this end, in this paper we propose a novel transformation of deadlines to priority-based DeLi2P model.

Deli2P collects user deadlines from devices. The modern electronic devices are fitted with timers to stop or start a device at a specific time. Similar to these timers in Deli2P consumer can select the time at which she requires the device's process to be complete by putting in the"putoff" time on the device or device plug interface. For example, if a consumer is putting in dishes for washing then the consumer can feed in 6 hours for the dishes to be washed and ready.

Deli2P transforms this deadline into a priority in the following way. The controller gathers three important parameters of a particular device. These parameters include operational time of a device, deadline of the operation and the time available before deadline, the "putoff". Based on these parameters it assigns priority to a device, which changes as time available approaches the deadline of operation. For example, a device with operational time of 2 hours has a deadline of operation 6 hours from the time the request was made. Using this information our controller computes the time available after every decision cycle in our algorithm as will be explained later. Priority assignment will be done using a mathematical function described in section 3 of the paper. With each device assigned a priority, based on the time available for execution we can aggregate the priority demands and schedule the device operation in the same way as done by Ranade and Beal (Ranade and Beal, 2010). If the device is not activated for operation in the current level of priority then it moves to a higher level. With higher priority level, the device has a higher chance of getting the activation signal. Priority level transition is done at equal time intervals based on time available which in this case is six hours divided into time periods of three hours (where 6 is the deadline and 3 is the number of flexible (Rehman et al.,) priority levels). This process is continued till the device is either operated or it is at the highest level where it is guaranteed execution.

When sufficient supply is available the system allows all the devices to execute as soon as they submit a demand to consume. As the demand grows above the supply, the devices with the least priority are instructed to "wait" for servicing based on a probabilistic model. This ensures that the demand never surpasses the supply. For example, in the early hours of the day when the demand is much less than supply and all devices are given go ahead for execution. But as the demand is about to cross the supply our algorithm puts each device in one of the flexible priority levels and let them change their state only when the demand-supply situation gets better or the deadline is close enough. Deli2P in this way is able to reduce the peak demand of the day while satisfying the consumer's preferences.

The rest of the paper discusses the related work in this area, our proposed solution, its model and finally a discussion on evaluation, conclusion and future work.

1.1 Related Work

Demand side management (DSM) techniques usually have one of the two goals: the first one is to reduce the electricity cost and the second is to reduce the peak load (Chai et al., 2014). A range of algorithms attempt to reduce the cost of electricity for the consumers. These include algorithms which incorporate the time of use pricing in reducing the cost of electricity of the consumer (Fan, 2011)(Lee and Lee, 2011), and DSM systems which maximizes the benefit of renewable energy sources for home consumer (Arif et al., 2013)(Daoxin et al., 2012). For these systems the goal is not overall supply-demand management but rather it is to minimize the cost of electricity to the consumer. However, this does not guarantee that the demand is shaped according to the global or utility's goals. To achieve this specific goals direct control systems are proposed which aim at reducing the peak load. The difference is that in the first category the goal is cost reduction and peak load reduction is implicit whereas in the second the peak load reduction is the goal and cost savings due to better load profiles are implicit.

The direct control algorithms thus control the consumer devices remotely. However, shutting down end user device is usually not very acceptable to the end users. This has been studied and expounded by many researchers (Kim and Shcherbakova, 2011). To capture the needs of the consumers there are two main processes proposed in the literature.

One stream of research for such DSMs is to gather the preferences or constraints of the consumers. That is, for each device the system predicts or collects from user the range within which the device can be scheduled. These constraint elicitation can be implicit as is the case Du and Lu (Du and Lu, 2011) and Molderink (Molderink et al., 2010) where forecasting and consumer profiling using sensors in the user premises are used to determine the constraints of the consumers. In other cases such as those proposed by Kim and Poor (Kim and Poor, 2011) and Arif and colleagues (Arif et al., 2013), the constraints are explicitly provided by the consumers through some interface. The authors of the systems argue that since we have knowledge of the consumer's constraints and schedule the devices accordingly, the DSM load management will be acceptable to the consumers.

However, as has been discussed by Molderink (Molderink et al., 2010), Arif (Arif et al., 2013) and Javed in AdOpt (Javed and Arshad, 2009), such scheduling is NP-complete (Ullman, 1975). To date there has been no polynomial time algorithm to solve the NP-complete problems. The only way to solve such problems is to enumerate all the possible combinations. But all combinations are exponential and thus planning for hundreds of thousands of devices is not possible. Use of artificial intelligence techniques such as genetic algorithms and ant colony optimization decrease the computation time but still take too long for large scale system scheduling and are known to be inaccurate.

The other stream is to allow the users to stipulate priority classes to devices or join the device to a contractual obligation group. ColorPower1 and ColorPower 2 allow the consumers to assign priorities to devices (Ranade and Beal, 2010; Beal et al., 2012). The system then manages the probability of execution for each priority class such that the demand shaping goals are reached while maintaining that the distribution is fair and according to consumer's priorities. Kim and Poor also proposed similar system however their grading of the devices was not as versatile(Kim and Poor, 2011). Pennywise on the other hand allow users to sign contracts with the utility. Since these contracts are standardized the utility can bunch together devices under similar contracts for computation. Escriva and colleagues also used such contracts for their proposed DSM strategy (Escriv-Escriv et al., 2010).

Since in these systems there is a natural way to combine the devices into consumption classes, the number of decision variable reduces to the number of consumption classes. For few hundred classes the existing algorithms are able to solve within a reasonable time as is shown by Javed and Arshad in AdOpt (Javed and Arshad, 2009).

However, since the priority systems observed by the authors are somewhat rigid. ColorPower, and Pennywise do not allow the consumers to change the priorities. Colorpower allows consumers to press an emergency button to explicitly demand electricity. However if priority of a device changes then this updation will take 24 hours to come into effect. Similarly re-negotiating contracts for Pennywise or in Escriva's system is a cumbersome task. As has been shown in UK's Power7 package, the consumers do not like to be bounded to certain priorities and contracts. As a biological being, the priorities and needs for the human consumer changes rapidly and regularly. The priorities for consumers are rarely consistent and fixed contracts do not do justice either.

To this end, in this paper we propose a transformation to convert a simple deadline based user feedback into a priority based system. Since we collect explicit preference and bound the system by it, we can reap the benefits of better user acceptability. Since we convert these preferences into priorities very similar to the ColorPower scheme, we can compute the solution in reasonably small time as well getting use the benefit of both the systems.

1.2 Proposed Solution

In this section we will first describe how our strategy consider consumers deadlines. Then we discuss how we have incorporated and improved existing ColorPower algorithm for our planning.

The goal of DSM is to control consumer devices to

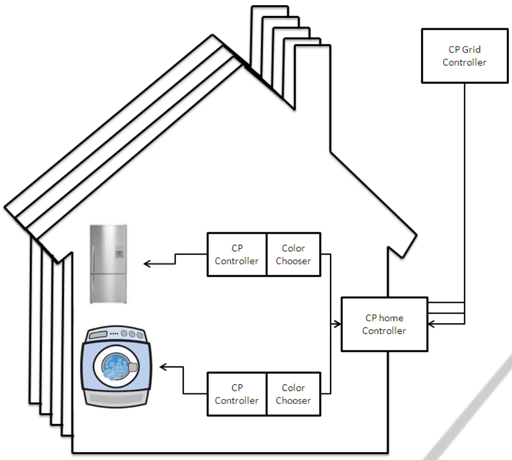

Figure 1: The architecture of the home system working with Deli2p and its interaction with the grid controller.

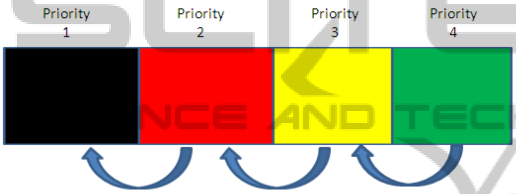

Figure 2: Priority scale for DeLi2P. As the deadline time approaches the priority color transitions from green to yellow to red and then black, the highest priority level.

reduce the electricity demand to specific thresholds. As previously discussed, there are two non-functional requirements of the DSM system, first is that it should be scalable and second it should be bound by the needs of the consumers. In this regard the priority based algorithms provide adequate solution for the first requirement. For instance, ColorPower is scalable, provides privacy preserving aggregation method and is fair in its distribution of electricity.

This algorithm operates in the following way. The controller assigns each device a color specifying its priority as shown in figure 2. At every heartbeat the home controller collects its demand from devices of each color. If two devices are yellow then it will add the demand of both devices as yellow. The algorithm provides for a grid wise aggregation mechanism whereby the grid controller has the aggregated demands for each of the four priority colors. The grid controller then assigns a probability to each priority color based on the supply demand equation. The policy is that the highest priority gets to use the supply till its demand is met. If supply is left then the lower priority is provided the supply. If for a priority level the supply is partial then each device in the priority is given a probability based on the amount of electricity available and the demand of that color. This way the

$$\Delta_i^{g-} = \begin{cases} 0 & \text{if } C^g \geq 0 \text{ or } i > b \\ |\hat{EF_i}| & \text{else if } \sum_{j \leq i} |\hat{EF_j}| \leq |C^g| \\ |C^g| - \sum_{j<i} |\hat{EF_j}| & \text{else if } \sum_{j<i} |\hat{EF_j}| < |C^g| \\ 0 & \text{otherwise} \end{cases}$$

Figure 3: ColorPower (Beal et al., 2012) controller for device.

$$p_{off,i,a} = \frac{\Delta_i^{g-} + \Delta_i^{p-} + \Delta_i^{c-}}{|EF_i|} \; ; \; p_{on,i,a} = \frac{\Delta_i^{g+} + \Delta_i^{p+} + \Delta_i^{c+}}{|DF_i|}$$

Figure 4: ColorPower (Beal et al., 2012) controller for the grid.

lower priority devices run on a probabilistic basis.

However, this scheme does not provide provisions for the consumer to constraint the load movement according to consumer's operations. If a consumer purchases a washing machine then she would wish to have the clothes washed within a specific period of time and if the algorithm does not provide this guarantee then the consumer will be tempted to bump up the device's priority to get the required service. This may result in spiraling up of priorities thereby leaving no space for optimization. Essentially the CP does not guarantee running a device even if the electricity is available.

DeLi2P uses the same efficient, scalable and fair ColorPower (CP) controllers to provide control of the device to the utility planner. One of the contributions and indeed an important contribution of our work is that instead of consumer assigning priorities we make these priorities adaptable in that the device controller adapts the devices' color according to the amount of time it has available to complete the task.

The difference is that when a consumer attempts to use a device, the consumer is provided with a timer to set the time of task completion. This can be achieved by installing a timer on the device. This maybe an external timer for legacy machine or it maybe an internal timer in the future smart devices however, discussion of its deployment is beyond the scope of this work. The consumer sets the time when she requires the task to be completed. Based on the time to deadline DeLi2P calculates the color of the device at runtime using the following formula:

$$C_i = \frac{\lceil (d_i - o_i) - curr \rceil}{len(k)}$$

Where d_i is the deadline set by the user, o_i is the operational execution time or the maximum time it will take the device to complete the task and *curr* is the current time. C_i is the priority color of the device at time *curr*. $len(k)$ is the length of interval that we give to each color.

As the time moves forward, that is the difference between $(d_i - o_i) - curr$ reduces, the priority of the device increase thereby increasing its chance to complete the task. The operational flow is similar to ColorPower except for the color assignment after each two minute period the color for the device is ascertained. If the consumer has asked for the device to operate and the operation has not yet started then the color is propagated to the CP home controller along with historical consumption value. The CP home controller aggregates the demand for each color, adds it to the data passed by previous house and passes it forward to next house so that it is transmitted to the CP Grid controller as shown in figure 1 and discussed in (Ranade and Beal, 2010). The CP grid controller based on its algorithm shown in figure 4 calculate the fractional part for each color. This value is passed to the CP Device controller and the device controller selects the state of the device using formula in figure 3

To illustrate the process, let us assume that a consumer attempts to use washing machine. The consumer wants the operation to be completed in 8 hours time and the operational execution time for the machine is 1 hour. Thus we have (8 - 1) hours to complete the task. This puts the device in yellow or category 3. Based on the global demand the CP grid controller assign probabilities to the colors and these probabilities are propagated to the CP device controllers. If at this time the supply is sufficient to supply yellow priority then this device will run immediately. But if yellow is partially supplied or not supplied at all then this device will use the CP controller using formula in figure 3. If the device gets a chance to run then it will execute otherwise it will wait till C_i is red. With an updated color the device's probability of execution will chance. If the supply is so short that even the red does not execute then 1 hour before the deadline device will turn black. Since black is emergency color the device will be provided with supply and the task will be achieved within the stipulated time. Figure 5 describes the aforementioned process as a flow chart.

1.3 Solution Model

In this section we model the demand of electricity according to its priorities. The time in our algorithm is divided into t time slices and we have j priorities. Demand of electricity for j priority class generated in a time slice t is given as:

$$\forall_j d_t^j = \text{Demand for } j^{th} \text{ priority at } t \text{ time}$$

For ColorPower, this will also be net demand or

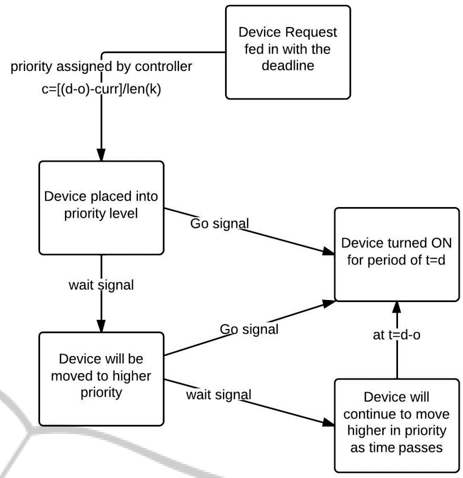

Figure 5: Flow chart describing the algorithm opertion on a single device.

D_t^j of the respective time slice and the priority class since there is no concept of carrying over load which has not been provided supply. But for DeLi2P, load which is not provided supply is considered is carried over thus net demand at time t for j priority class is:

$$\forall_j D_t^j = d_t^j + (D_{t-1}^j \times p_{t-1}^j + \Delta_t^{j-1}) - \Delta_t^j$$

Here Δ_t^{j-1} is the demand for the lower priority level which has expired and needs to elevated to the next level and Δ_t^j is the expired demand from j^{th} level which needs to be elevated to the $j+1^{th}$ level.

p_t^j is the probability of selection for the j^{th} priority at time t. DeLi2P and ColorPower use the same formulation for calculating p_t^j gieven as:

$$p_t^j = 1 \text{ if } \sum_{i=j}^{max(j)} D_t^i \leq S$$

$$p_t^j = 0 \text{ if } \sum_{i=j+1}^{max(j)} D_t^i \geq S$$

$$p_t^j = \frac{S - \sum_{i=j+1}^{max(j)} D_t^i}{D_t^j} \text{ otherwise}$$

Where S is the total supply to the system.

The graphs in figure 6 show this transformation of priority level induced by the transfer of Δ load from load priority levels to higher levels. Initial priority levels in form of colors are shown in figure 7. Though the probability assignment in ColorPower and DeLi2P is same, the underlying total demand D_t^j varies in DeLi2P to incorporate the concept of deadline but in ColorPower, the deadline is not accommodated. With this strategy a peak reduction of up to

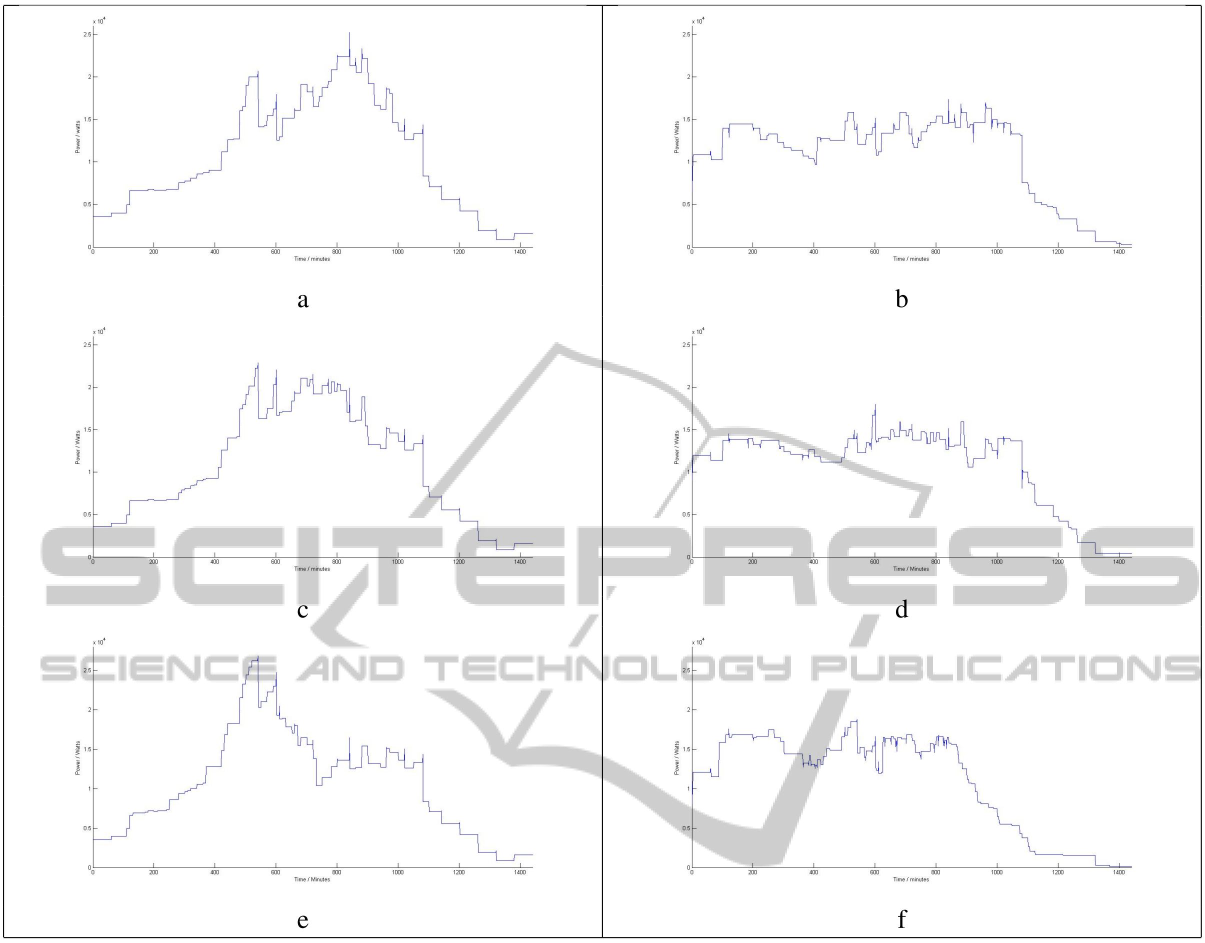

Figure 6: Graphs showing demand and DSM through DeLi2P results. On the left the graphs show the demand for the day and on the right the demand after application of DeLi2P. The peak demand ranges from 26MW on day 3 to 23MW on day 2. on all these days DeLi2P has restricted the peak demand to 18MW without violating consumer deadlines. x-axis shows time in minutes while y-axis shows power consumption in watts.

30% is achieved with minimum missed deadlines thus ensuring user satisfaction.

2 EVALUATION

Our evaluation comprise of three steps: In the first step we show the working of Deli2p as a case study for one house consisting of four devices. The main objective of this demonstration is to show the color transition feature of Deli2p. In the second step we show the evaluation of Deli2p for one hundred devices under various deadline constraints and user priorities. In the third step we compare Deli2p with ColorPower algorithm and show their comparative effectiveness and peak shaving ability.

2.1 Experimental Setup

To carry out analysis, simulations for the proposed algorithm and related work were developed in C# programming language. These simulations were conducted on Intel i5 Processor with 4GB of physical memory having 2.4GHz of clock speed. Power consumption data for 100 different devices was used in simulations for extensive testing of algorithms. The data is generated at the rate of 2 samples / minute by the configurable simulator presented in (Arshad et al., 2013). The aggregated consumption of each device at a articular time window was used to compute average power for that specific appliance. The average powers were then put to use in demand response algorithms corresponding to the time window for which they were computed to obtain results close to the actual environment.

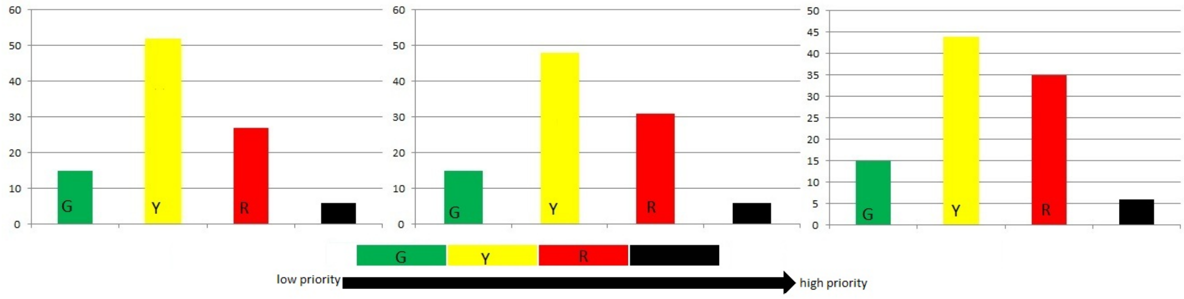

Figure 7: Initial priority levels assigned to devices on Days 1, 2 and 3 respectively from figure 6. These priority levels change over the course of 24 hrs based on the supply demand situation.

2.2 Case Study of DeLi2P for One House

In this case study we show the operation of 4 devices for a single household. All four devices' requirements are fed to the system at the same time. As shown in figure 8 when the device operational request is fed in our system, the controller assigns priority based on deadline and duration. The probabilistic model then sends it turn ON or OFF signal. If the device turns ON it completes its operation in a single time period, as seen for device 4 in this case. However, failing to do so causes device transition to a higher priority level. As it can be seen from this table that device 1 is first in a least prior GREEN mode. Since it does not get activated it moves to higher priority until eventually at time $t = d_i - o_i$ (d_i is the deadline of ith device and o_i is the operational time of ith device) it enters BLACK mode where it is applied turn ON signal to ensure execution of operation for that particular device before the deadline. After it has completed its operation the device turns white indicating the operation has been accomplished.

2.3 Applying DeLi2P to One Hundred Devices

In our evaluation above, we expand our algorithm on a pool of 100 devices which are assigned operational duration and putoff time. The figure 9 shows one case in which devices are activated by scheduling their deadlines into priority levels. Based on Power demand-supply equations explained earlier our probabilistic model turn on the devices without exceeding total supply. The devices which are not operated eventually move into higher level of priority i.e from Green to Yellow to Red. However, if a device fails to activate within flexible priority levels it enters BLACK category in which each device is given turn on signal to make sure no device goes non-operated in order to achieve consumers‘ satisfaction

In this section we show the results of applying DeLi2P for one hundred devices. As described earlier, when a consumer attempts to use a machine the system asks the consumer to provide a deadline by which time she requires the task done. Based on the available time the algorithm assigns an initial priority level to the device. Considering the overall supply-demand equation, the device is run when its deadline is near or earlier if there is enough electricity available.

The results of application of DeLi2P are shown in figure 6. The graphs on the left show the demand of the system without DeLi2P and on the right the results are with DeLi2P with 18000 KW (18MW) as the target maximum load. As can be seen, DeLi2P is able to maintain this target even though the demand ranged from 25 MW on day 3 to 23 MW on day 2 while satisfying the deadlines set by the consumers.

2.4 Comparison of DeLi2P with ColorPower

To illustrate on grid let us consider the demand in figure 10(a). This is a hypothetical but realistic demand where each of the priority level is equally divided. This is the demand that was assumed by ColorPower algorithm authors for their validation (Ranade and Beal, 2010). The second figure 10(b) shows the response of ColorPower and similar algorithms. As can be seen the demand is flat lined at demand of 140 units. This may result in a yellow device to be unavailable for as much as 20 hours. To ameliorate this situation in figure 10(c) the response of DeLi2P is shown. As the time moves forward DeLi2P elevates the priority of yellow, green and red. This elevation of priority means that the device has the opportunity to run within the deadline constrain set by the consumer. the deadline will fail only when a part of black is above the threshold line. This in essence is the breaking point of the algorithm, that is, if we require to shut down devices in black then the dead-

Time / hour	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Device 1	G	G	G	G	G	Y	Y	Y	Y	Y	Y	R	R	R	R	R	R						W	W
Device 2	Y	Y	Y	Y	Y	Y	R	R	R	R	R	R	R	R				W	W	W	W	W	W	W
Device 3	R	R					W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W
Device 4	R	R	R	R	R	R	R	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W

	Deadline / hours	Duration / hours		
Device 1	23	5	G	Green
Device 2	18	3	Y	Yellow
Device 3	9	4	R	Red
Device 4	13	5		Black
			W	White

Figure 8: . This figure shows how colors are changed for a 24 hours period for four devices in a house depending on their priority and how close they are to their deadline.

Time/hour	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Black	46	40	39	34	42	37	29	22	20	16	13	13	12	14	18	14	16	18	16	15	9	6	3	0
Red	0	0	0	0	0	2	9	18	23	23	23	26	25	22	14	15	11	7	4	1	0	0	0	0
Yellow	38	38	38	38	28	27	23	16	11	11	11	6	4	3	2	3	2	3	2	1	1	0	0	0
Green	15	15	15	15	15	10	7	5	5	5	5	5	5	5	5	3	3	1	0	0	0	0	0	0
Accomplishments	1	7	8	13	15	24	32	39	41	45	48	50	54	56	61	65	68	71	78	82	90	94	97	100

Figure 9: This figure shows the working of Deli2p with one hundred devices over a 24 hours period. The algorithm starts of by putting the devices in one of the priority and changes the priority as the deadline is close.

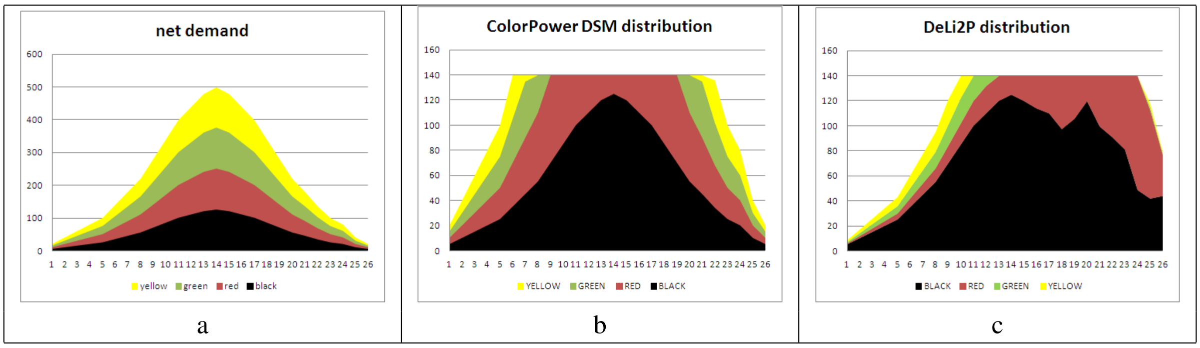

Figure 10: Graphs showing net demand, demand shaping through ColorPower and through DeLi2P.

lines for those consumers will be violated. In comparison ColorPower does not cater for this situation hence evaluating it for deadline failure is not possible.

3 CONCLUSION AND FUTURE WORK

The need to incorporate consumer's priorities and requirements in to demand side management system is critical to its acceptance and thereby its use. In this paper we have considered two key requirements for increasing the acceptability of the consumer. First we have provided a way for the consumer to be an active part of the DSM. This provides satisfaction to the consumer as proposed by Breukers and colleagues (Breukers et al., 2001). Secondly, we have provided a way for the consumer's deadlines to be catered for in a scalable manner by converting those deadlines to priority levels and thereby making the algorithm scalable, secure and fair as well.

We see this as a viable solution for future DSM systems. The future of this work is to apply it to a residential area and observe the consumer's response to this strategy. A second path of research is to incorporate machine learning to learn consumer behavior in order to automate the timer task in order to aid the consumer. Yet another possibility is to incorporate time of use pricing in this system such that the consumer is informed of the price savings that she can achieve by setting the timer to a later time.

ACKNOWLEDGEMENT

This work is in part supported by grants from the Department of Computer Science at LUMS, and ICT Research and Development Fund of Pakistan.

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