Industrial Power Demand Response Analysis for One-Part Real-Time Pricing

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Abstract– **Demand-side management (DSM) programs in the industrial sector appear to be economically feasible due to the large controllable loads and relatively low costs per control point. Innovative electricity tariffs provide one of the most important DSM alternatives. Because real-time pricing (RTP) is considered as an excellent management option which reflects the real cost of generating electricity to the end user, the electricity cost saving potential of RTP through demand management is presented in this paper. A unique analytical approach is followed to describe the potential electricity cost savings mathematically in terms of variables familiar to both the end user and utility. These variables include the installed power consumption capacity of the plant, the plant's spare energy consumption capacity, and terms that describe the structure of the RTP tariff.**

I. INTRODUCTION

Since the introduction of DSM in the 1970's, load management projects mainly concentrated on residential loads. Some of the projects have resulted in a fair profitability, but many of the programs have not succeeded in achieving the established objectives, mainly due to the size of load per control point. Björk [1] stated that it is likely that applications with low cost per controlled load may be found in industry, where the controllable load per control point is relatively large. Flory et al [2] reported that at many utilities 2-10% of the industrial customers account for at least 80% of the electricity usage, which emphasises the economic feasibility of DSM programs in the industrial sector. In the South African situation the industrial load dominates, which motivated the local utility, ESKOM, to introduce a Key Customer focus group to promote marketing and customer services to its large industrial customers. In the view of these observations, this study focuses on demand management in the industrial sector.

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The formulation of utility DSM goals is largely influenced by the utility's characteristics and external operating environment. Although utilities can offer a wide range of inducements and incentives to encourage customer participation in a particular DSM program, ultimately it is the customer decision to participate which influences the success of the activity. DSM approaches and techniques should involve a partnership between the utility and its customers, seeking common ground to maximise mutual benefit. This process will eventually lead to a customised pricing agreement between a supply utility and a customer who is willing to participate in the DSM program.

Parties involved in a customised pricing process should be aware of the structures of various tariff options, and they should have knowledge of the possible impact of these DSM tariffs on the performance criteria of both the utility and the customer.

Although time of use (TOU) pricing represented a significant step towards efficient electricity pricing, there is a growing recognition that dynamic tariff forms can be more efficient. Dynamic pricing broadly encompasses tariff structures that have one or more elements which can be calculated and posted close to the time of applicability [4]. This definition embraces several concepts developed in the pricing literature, such as real-time (spot) pricing and other forms of "innovative" rates. The theory behind this pricing strategy is well documented [5].

By reflecting the "real" cost of electricity to the consumer through variable prices for specific - generally one hour - time periods, the utility provides the consumer with the information necessary to make economically sound load management decisions. Benefits of spot pricing for a customer are shown to increase with [3]:

- the magnitude of price changes over time;
- the magnitude of the customer's storage capacity;
- the amount of his peak production capacity.

These observations were made in [3] by means of a linear program (LP) based optimisation algorithm. The purpose of this paper is to add more insight into the electricity cost saving potential of real-time pricing (RTP) through intelligent demand management. The analytical approach as illustrated, will enable utilities and industrial end users of electricity to acquire a better knowledge of the benefits that RTP can offer.

One of these benefits, i.e. the electricity cost saving potential, will be addressed in this paper. It will be mathematically presented as a function of variables that describe the structure of the real-time prices, as well as the configuration of the industrial plant, which includes the spare energy consumption capacity of the end user and the installed power consumption capacity. This approach is unique and contributes to knowledge in this field of research.

A load scheduling strategy which may result in minimum electricity costs to the end user, is presented in section II. The feasibility of the strategy depends on certain assumptions, which will be given. The mathematical modelling of the price duration curve (hourly marginal rate duration curve) is introduced in section III. In section IV mathematical expressions of the electricity costs of an end user under one-part RTP tariff structures are derived. Section V presents the mathematical expression of the electricity cost saving potential under RTP, together with some case studies to graphically display the impacts of some important factors on the saving potential. Conclusions follow in section VI.

II. OPTIMAL LOAD SCHEDULING STRATEGY

An industrial end user of electricity that is able to curtail processes on short notice in order to respond to hourly varying energy tariffs, may be able to benefit from RTP. By assuming:

- that the plant has adequate installed storage capacity or spare energy consumption capacity;
- that no losses due to load scheduling occur;
- that the demand levels of the individual controllable processes in the plant can be controlled, without constraints, between a maximum level P_{max} and a minimum level P_{min};
- that each individual controllable process has a certain constant base power (or power loss component) P_{loss} that does not contribute to any production;
- that the same production target should be reached under controlled and uncontrolled conditions within the same time horizon of H hours;
- that an amount of E kWh of electrical energy is required to produce the required production target;
- that a one-part RTP structure is considered without a fixed cost component (thus only marginal rates apply).

The total electricity costs EC (in cents) over H hours of production can be given as:

$$EC = x_1 \cdot hmr_1 + x_2 \cdot hmr_2 + \cdots + x_H \cdot hmr_H \qquad (1)$$

where x_i represents the total hourly power consumption (actually the average of hourly power) of the processes in hour i, while hmr_i is the hourly marginal rate (in c/kWh) of the RTP tariff structure in hour i. The aim is to find the values of x_i which will minimize the objective function in (1) subject to the following set of linear constraints:

$$\begin{aligned}(x_1 - b) + (x_2 - b) + \cdots + (x_H - b) &= E \\ x_1 + x_2 + \cdots + x_H &= E + b \cdot H\end{aligned} \qquad (2)$$

and

$$P_{min} \le x_i \le P_{max} \quad , \quad i = 1,2,3,\cdots,H \qquad (3)$$

where b is the total hourly non-productive power (or base power) which is assumed to be constant over time. By means of an upper-bounding dual linear programming algorithm [6] it has been shown that the minimum electricity costs will be obtained if the processes' power demand levels are either at P_{min} when hourly rates are high, and at P_{max} when the hourly rates are low - a result which can be expected as the optimum feasible solution of a LP problem will be on the boundary of the feasible region, which is partly given by (3).

There exists a certain hourly marginal rate cut-off value, HMR_{cut}, which will provide the threshold price above which the power levels should be shut down to P_{min}, and below which the power levels should be set at P_{max}.

An hourly marginal rate duration curve (HMRDC) can be used to graphically display this concept and to form the basis of the mathematical expressions which will follow. Fig. 1 illustrates actual discrete hourly marginal rate (hmr) values for H hours, sorted from the highest to lowest value to form the discrete HMRDC. The corresponding power demand levels according to the proposed optimum scheduling strategy are shown together with a non-chronological cut-off hour, H_{cut}, where "transition" occurs between the P_{min} and P_{max} levels. When this value of H_{cut} is projected upwards to the HMRDC, the value of HMR_{cut} can be read from the duration curve.

It is evident from Fig. 1 that the shape of the HMRDC as well as the value of H_{cut} will have an influence on the value of HMR_{cut}, which will have a large impact on the electricity costs of the end user. It will be convenient to develop a mathematical expression for the HMRDC which will describe the hourly marginal rates as a continuous function of non-chronological hours h. This expression will be used later to determine the potential electricity cost savings under RTP.

III. MODELLING OF THE HMRDC

The load duration curve (LDC) offers a tool by which DSM impacts can be quantified into power system planning and operation. Models of the LDC provide one of the most important tools in the analysis of electric power systems. There are several methods attempting to express the LDC mathematically and a recent report [7] presented an analytical approach which appears to give credible results.

Based on this analytical method, a model of the HMRDC is derived [8]. With this model the non-chronological hourly marginal rates $hmr(h)$ are described in terms of four principal

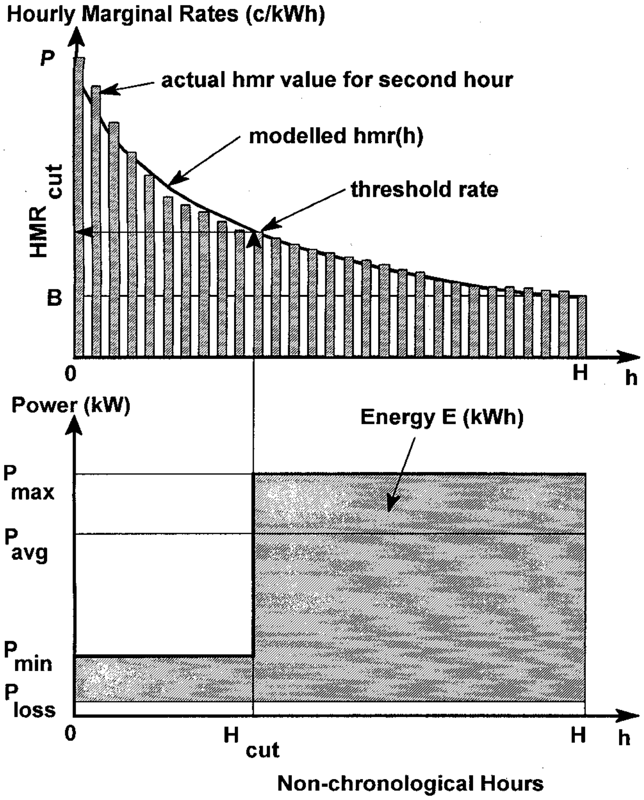

Fig. 1. HMRDC and corresponding optimal power demand levels

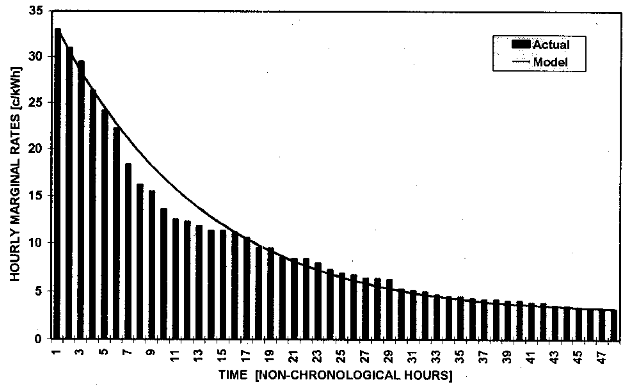

Fig. 2. Actual and modeled hourly marginal rate duration curves

parameters of the HMRDC, i.e. the peak hour marginal rate P, the base hour marginal rate B, the time horizon H, and the average value of the hourly marginal rates over H hours, $\overline{hmr}$. The last term is directly proportional to the area underneath the HMRDC.

The resulting mathematical expression is given as [8]:

$$hmr(h) = B + (P - B) \cdot \left(1 - \frac{h}{H}\right) exp^{\frac{C \cdot h}{H}} \quad [c/kWh] \quad (4)$$

where C is the curve shape factor. The curve will have a concave shape when $C < 0$ (like the one shown in Fig. 1), a convex shape when $C > 0$, and a linear shape with a negative slope when $C = 0$. The value of C is given as [8]:

$$C = \sum_{n=1}^{7} R_n \cdot \left[\frac{\overline{hmr} - B}{P - B} - \frac{1}{2}\right]^n \quad (5)$$

where the values of R_n are the same as that derived in [7]. The modelled curve will always intersect with co-ordinates $[hmr(h), h] = [P, 0]$ and $[B, H]$. With reference to Fig. 1, for the same value of H_{cut}, different values of the shape factor C will result in different price threshold values.

Fig. 2 illustrates an example where a set of actual hourly marginal rates is modelled in a duration curve. In this case P = 33 c/kWh, B = 3.2 c/kWh, H = 48 hours, $\overline{hmr}$ = 10.02 c/kWh, and C = -2.944.

By inspection of Fig. 1, the total energy E required (in kWh) within H hours to reach the production target is given as:

$$E = H \cdot (P_{max} - P_{loss}) - H_{cut} \cdot (P_{max} - P_{min}) \quad (6)$$

from which H_{cut} (in non-chronological hours) is derived as:

$$H_{cut} = \frac{H \cdot (P_{max} - P_{loss}) - E}{P_{max} - P_{min}} = \frac{Q}{P_{max} - P_{min}} \quad (7)$$

where Q is the total spare energy consumption capacity (in kWh) of the controllable processes. If no load scheduling is applied, it is assumed that the plant has to operate on a constant power demand level of P_{avg} to produce the same production target in H hours. This value will be between P_{min} and P_{max}, with the same area E underneath the power curve.

$$P_{avg} = P_{loss} + \frac{E}{H} = P_{loss} + \frac{H \cdot (P_{max} - P_{loss}) - Q}{H} = P_{max} - \frac{Q}{H} \quad [kW] \quad (8)$$

IV. ELECTRICITY COSTS TO THE END USER WITHOUT LOAD SCHEDULING

The basic structure of a one-part RTP consists of marginal energy rates applicable to the hourly energy consumption of the end user. If one considers no load scheduling operation, and assumes that the plant operates at a constant power demand level of P_{avg} to produce the production target, an expression for the electricity costs EC_{nls} (in cent) is given in (9) by using (4) and (8) (the footnote *nls* denotes *no load scheduling*). The non-linear dependency of the electricity costs to the parameters of the hourly marginal rates is evident from (9), while it is linearly dependent on the spare energy consumption capacity Q of the plant.

$$EC_{nls} = \int_0^H P_{avg} \cdot hmr(h)\, dh = \left[\frac{H \cdot P_{max} - Q}{C^2}\right]\left[B \cdot C^2 + (P-B)(exp^C - C - 1)\right] \tag{9}$$

V. ELECTRICITY COST SAVING POTENTIAL

When the end user is applying optimum load scheduling operation as proposed earlier, an expression for the electricity costs under load scheduling operation, EC_{ls}, (in cent) is given in (10) (where the footnote *ls* denotes *load scheduling*).

$$EC_{ls} = \int_0^{H_{cut}} P_{min} \cdot hmr(h)\, dh + \int_{H_{cut}}^{H} P_{max} \cdot hmr(h)\, dh$$

$$= \frac{P_{max}}{C^2}\left[B \cdot C^2 \cdot H + H(P-B)\, exp^C\right] - \frac{P_{min}}{C^2}\left[H(P-B)(C+1)\right] + \left[\frac{P_{max} - P_{min}}{C^2}\right] \times \left[(P-B)(C \cdot H_{cut} - C \cdot H - H)\, exp^{\frac{C \cdot H_{cut}}{H}} - B \cdot C^2 \cdot H_{cut}\right] \tag{10}$$

The potential electricity cost savings *ECS* (in cent) to the end user are the difference in electricity costs between scheduled and unscheduled operation.

$$ECS = EC_{nls} - EC_{ls} \tag{11}$$

The expression for the percentage electricity cost savings *%ECS* is given as:

$$\%ECS = 100 \cdot \frac{ECS}{EC_{nls}} = 100 \cdot \left[1 - \frac{EC_{ls}}{EC_{nls}}\right] \quad [\%]. \tag{12}$$

By substituting (9) and (10) into (11), the following results:

$$ECS = \left[\frac{P_{max} - P_{min}}{C^2}\right]\left\{(P-B)\left[\begin{array}{l} H(C+1)(exp^{\frac{C \cdot H_{cut}}{H}} - 1) \\ \cdots - H_{cut} \cdot C \cdot exp^{\frac{C \cdot H_{cut}}{H}} \end{array}\right] \cdots + B \cdot H_{cut} \cdot C^2\right\} \cdots - \frac{Q}{C^2}\left[B \cdot C^2 + (P-B)(exp^C - C - 1)\right] \quad [cent]. \tag{13}$$

The variable H_{cut} is a function of the spare energy consumption capacity *Q* and can be substituted by (7) into (13). It is evident that the following factors will have an influence on the value of *ECS*:

- the production target which will determine *E*;
- the peak installed power consumption capacity P_{max};
- the difference between P_{max} and P_{min};
- the length of the production period *H*;
- the spare energy consumption capacity *Q*, which mainly depends on *E*, P_{max} and *H*;
- the shape of the HMRDC, which depends on the curve shape factor *C*. The shape factor *C* depends on:
  - ◊ the peak hour marginal rate *P*;
  - ◊ the base hour marginal rate *B*; and
  - ◊ the average of the hourly marginal rates $\overline{hmr}$.

Equation (13) is rather complex and it is difficult to understand the impacts of the mentioned variables on the value of *ECS*. Some case studies will be given to graphically illustrate the potential electricity cost savings. Consider five possible shapes of the HMRDC. The average value for each curve is the same, i.e. $\overline{hmr}$ = 5.95 c/kWh. The base marginal rate *B* of each curve is 3 c/kWh. *H* = 168 hours.

Fig. 3 illustrates these curves with peak marginal rate values as follows: *C* = -7.31, *P* = 33 c/kWh; *C* = -1.813, *P* = 12.95 c/kWh; *C* = 0, *P* = 8.91 c/kWh; *C* = 0.498, *P* = 7.97 c/kWh, *C* = 1.056, *P* = 7.03 c/kWh.

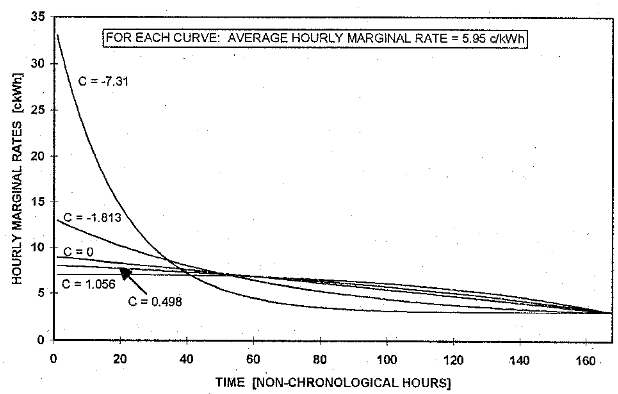

Fig. 3. Modeled HMRDCs for five values of *C*

A. Case Study 1

Consider a fictitious plant with P_{max} = 100 kW, P_{min} = 30 kW, and P_{loss} = 30 kW. The maximum installed energy consumption capacity E_{max} available to produce products in *H* hours is:

$$E_{max} = H \cdot (P_{max} - P_{loss}) \qquad [kWh] \tag{14}$$

while the maximum spare energy consumption capacity Q_{max} over that period is:

$$Q_{max} = H \cdot (P_{max} - P_{min}) \qquad [kWh]. \tag{15}$$

From (14) and (15):

$$\frac{Q_{max}}{E_{max}} = \frac{P_{max} - P_{min}}{P_{max} - P_{loss}}. \tag{16}$$

By substituting the given power ratings of this fictitious plant

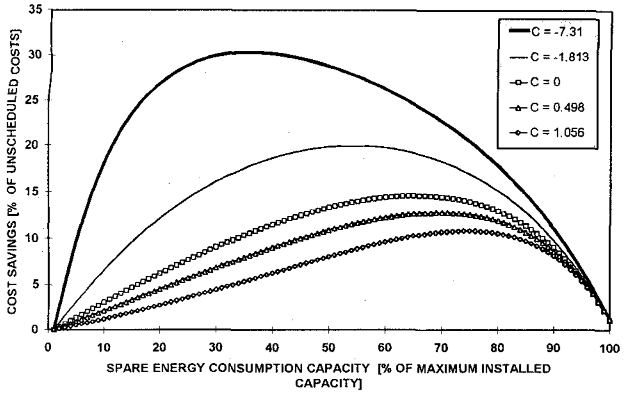

Fig. 4. Percentage cost savings vs. spare energy consumption capacity (parameter C is varied and $P_{min} = P_{loss} = 30\%$ of P_{max})

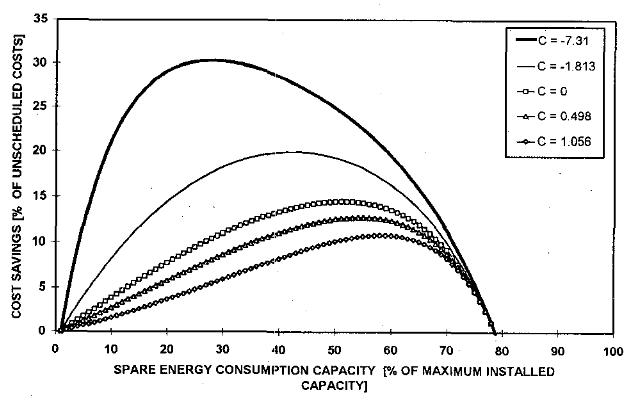

Fig. 5. Percentage cost savings vs. spare energy consumption capacity (parameter C is varied, $P_{min} = 30\%$ and $P_{loss} = 10\%$ of P_{max})

into (16), the maximum spare energy consumption capacity of the plant is 100% of the available installed energy consumption capacity. Fig. 4 displays the percentage electricity cost savings to an end user as a function of spare energy consumption capacity Q. Five curves are displayed which represent the five possible HMRDCs under consideration.

It is clear that a large concave HMRDC ($C << 0$) will result in the highest cost savings, especially when the end user has spare energy consumption capacity of between 10 and 80%. A power system that is experiencing relatively high loss of load probability (LOLP) values may result in HMRDCs with large concave shapes (relatively low marginal rates for most of the time, with a few exceptionally high marginal rates caused by high LOLP values). Refer to [5] for more detail on LOLP and the theory of spot-pricing.

By logic reasoning no cost savings are possible when the plant has zero spare energy consumption capacity, or at 100% spare energy consumption capacity when no electricity costs are incurred because there is no production. This is also evident from Fig. 4.

B. Case Study 2

The same as the previous case, but $P_{loss} = 10$ kW. Equation (16) now indicates that the plant has a maximum spare energy consumption capacity of 78% of the maximum installed capacity. No cost savings are possible beyond that level. Fig. 5 displays the percentage electricity cost savings for this case. The shapes and magnitudes of the curves look similar to the previous case, but the range of spare energy consumption capacity where savings can be incurred is narrower. It is again obvious that the HMRDC with a large concave shape ($C = -7.31$) will result in the maximum possible cost savings.

C. Case Study 3

The same as in case 1, except that $P_{min} = P_{loss} = 0$ kW. This may represent the case where the base load and loss of the plant's process(es) are negligible and the process(es) can be curtailed completely ($P_{min} = 0$ kW).

The larger difference between P_{max} and P_{min} results in higher percentage cost savings, which is evident from Fig. 6 and the first term in (13). Again the large concave shaped HMRDC ($C = -7.31$) will result in the largest cost savings over a wide range of spare energy consumption capacity.

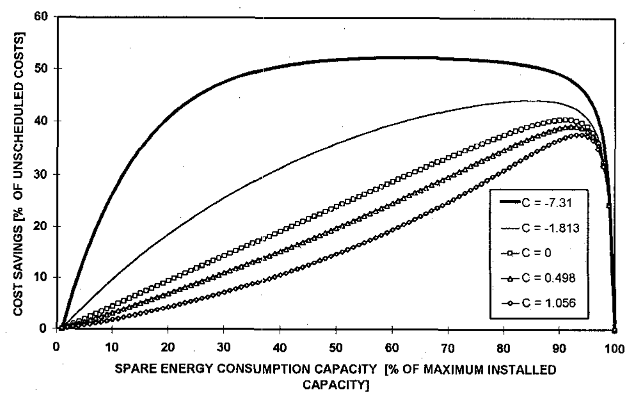

Fig. 6. Percentage cost savings vs. spare energy consumption capacity (parameter C is varied, and $P_{min} = P_{loss} = 0\%$ of P_{max})

D. Case Study 4

As in case 1, $P_{max} = 100$ kW, $P_{min} = P_{loss} = 30$ kW. The aim of this case study is to investigate the impact of the average of the hourly marginal rates, $\overline{hmr}$, on the potential electricity cost savings. The shape factor of each of the five HMRDCs is taken the same, i.e. $C = -7.31$, while $B = 3$ c/kWh for each curve. However, the peak rate, P, varies for each curve to result in a different average value for each curve. Higher average values of the hourly marginal rates over a period of H hours will result in higher percentage electricity cost savings, *%ECS*, as is displayed in Fig. 7.

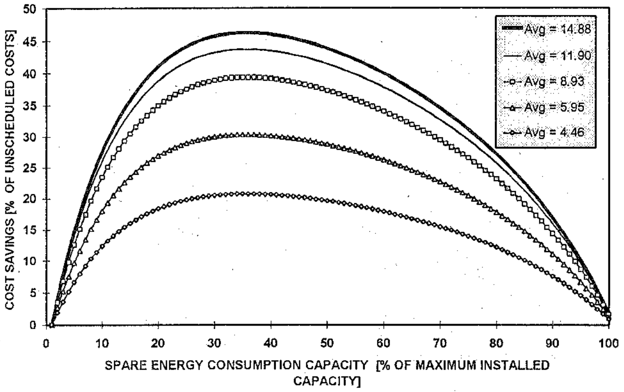

Fig. 7. Percentage cost savings vs. spare energy consumption capacity (parameter P is varied, and $P_{min} = P_{loss} = 30\%$ of P_{max})

VI. CONCLUSIONS

Based on a number of assumptions, an optimal load scheduling strategy was proposed to minimize the electricity costs of an industrial end user under one-part RTP. A method was presented which may be used by an industrial end user to respond adequately to real-time electricity prices. With the aid of an hourly marginal rate duration curve the threshold value of the hourly marginal rates can be determined where the end user should control his loads.

An analytical approach was followed to describe the potential electricity cost savings to an industrial end user under RTP through intelligent demand management. Mathematical expressions are given to describe the cost savings in terms of a number of variables familiar to the end user and utility. These variables include the plant's installed power consumption capacity, the spare energy consumption capacity and terms which describe the structure of the RTP tariff. Although idealised to some extent because of the number of assumptions that have been made, these mathematical expressions may provide valuable insight into the demand response potential of an end user under RTP.

Future work may involve similar approaches to quantify the cost of unserved energy (CUE) which may result from demand management actions under RTP. The CUE may consist of components (damage functions) such as the cost of production losses due to inadequate storage capacities, the cost due to switching losses (e.g. process restart costs), etc. Eventually the economic value of RTP may evolve as the difference between the potential electricity cost savings and the cost of unserved energy due to demand management. The economic value of RTP will serve to indicate to the utility and end user whether RTP will be a feasible DSM tariff alternative to implement at the end user's plant.

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