A decision support algorithm for assessing the engagement of a demand response program in the industrial sector of the smart grid

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ABSTRACT

In the industrial sector of the smart grid (SG), a demand response program (DRP) is offered to consumers to motivate them to shift their demand for electricity to the off-peak period. DRP can cause a dilemma for industrial consumers when energy load is decreased since it may disrupt the production process and they may consequently incur losses. Hence, industrial units may choose to accept or reject a DRP. If they choose to engage in a DRP, they may use the available back-up on-site energy resources to access the required amount of energy. Hence, any decision about load curtailment requires a comprehensive assessment of all layers of production and operational management. This paper utilises several methodologies to evaluate the effects of DRP engagement on operational management. Firstly, the Delphi method is employed for extracting and identifying twenty-six criteria embedded in ten operational and production management factors. Secondly, based on these criteria, the production equipment is ranked using the TOPSIS method. This ranking shows which equipment will have less impact on the organisation's profit as a result of participating in a DRP; but, it will not support production and energy planning which is affected by DRP engagement. So, thirdly, a linear programming (LP) model in a discrete scheduling time horizon is proposed which considers the TOPSIS method output and all the constraints imposed by the DRP and the production resources. Finally, based on the proposed methodology, a decision-making algorithm is designed to assist the operation and energy managers to decide whether to accept or reject the offer to engage in a DRP and if they decide to participate, how to best utilize the available distributed energy resources to regain the energy lost. The main contribution of this paper is the proposed methodology which combines the outcome of the Delphi and TOPSIS methods with a linear optimisation model, the effectiveness of which is clearly demonstrated by the sensitivity analysis.

Keywords: Demand response program, energy management, smart grid, TOPSIS, production energy planning, Delphi method, linear programming, decision making, and optimisation.

1. Introduction

In the smart grid (SG), demand-side management (DSM) comprises those technologies, activities and strategies used by the utility provider on the demand side of the energy network to manage load, improve energy efficiency, reduce emissions, and increase consumer participation in energy management. The main aim of DSM is to balance demand with available supply instead of the conventional policy where energy is supplied to meet demand (Warren 2014). SG consumers are residential, commercial, municipal, or industrial, the latter being the focus of this paper since it consumes the largest share of total energy consumption (Palensky & Dietrich, 2011). For example, in 2011-12, Australia's manufacturing sector was the largest user of electricity with 43.6% (or 67,400 GWh) of electricity consumption and 27.3% (or $5.5b) of total electricity expenditure (ABS, 2013). The demand response program (DRP) is a DSM method by which electricity aggregators or utilities can manage power consumption via price-based or incentive-based regulations, benefitting participants who curtail their energy demand during peak periods or shift their demand to off-peak periods (Palensky & Dietrich, 2011; Siano, 2014).

DRPs are categorised as either incentive-based or time-based programs (IBP, TBP), as shown in Table 1. In IBPs, participants are rewarded based on their consumption behaviour performance in critical conditions by receiving discount rates or credits on their bill. In TBPs, electricity tariffs are based on dynamic pricing rates that fluctuate according to the real-time cost of the electricity market (Albadi & El-Saadany, 2008). The methodology proposed in this paper is based on real-time pricing (RTP) which is the most efficient and direct program in the competitive energy market. A participant of real-time pricing is informed of the energy prices which reflect the real cost of energy in the wholesale market on a day-ahead or an hour-ahead basis (Aghaei & Alizadeh, 2013; Albadi & El-Saadany, 2008). An interruptible load program is a contract between the aggregator and consumers. It defines a special tariff as a rate discount if consumers reduce and regulate the load when the utility faces a system contingency situation. Time-of-use pricing refers to different electricity prices for different periods of time. This DRP reflects the average cost of power generation and delivery for each time interval (Aghaei & Alizadeh, 2013; Albadi & El-Saadany, 2008).

Table 1
Demand response programs.

Incentive-Based Programs	Time-Based Programs
1. Demand Bidding and Buyback 2. Direct Load Control 3. Emergency Demand Response 4. Interruptible Load 5. Load as Capacity Resource 6. Non-Spinning Reserves 7. Regulation Service 8. Spinning Reserves	1. Critical Peak Pricing with Control 2. Critical Peak Pricing (CPP) 3. Peak Time Rebate 4. Real-Time Pricing (RTP) 5. Time-of-Use Pricing (TOU) 6. System Peak Response Transmission Tariff

In the industrial sector of the SG, offering commercial incentives to shift power demand to off-peak periods can cause a dilemma, since a DRP may disrupt the production process and the organisation may incur losses if its energy load is decreased. However, principally, in electricity demand economics, the more electricity that is consumed, the more products are produced. In production functions, the production output, such as sales income, profit, and added value are positively correlated with electricity consumption as an input (Hu & Hu, 2013). However, most industrial consumers are equipped with on-site energy generators for an emergency back-up or auxiliary power for the DRP (Siano, 2014). Hence, industries could consider one of the following options:

a) rejecting a DRP, sustaining production during on-peak periods, and accepting high energy prices and penalties;
b) engaging in a DRP and being compensated for lost production by receiving discounts on the energy price rate or accepting a commercial incentive;
c) engaging in a DRP and using back-up on-site energy generators during peak hours and/or a storage system to regain the energy lost;
d) engaging in a DRP and curtailing energy consumption during peak hours by shifting loads to off-peak periods and employing an economically and technically viable energy plan.

In addition to choosing the strategy most appropriate for production, there should be adequate information and communication technologies (ICT) and an advanced metering infrastructure (AMI) to provide precise and real-time information for energy-efficient decision-making (Karlsson, 2011; Rashed Mohassel, Fung, Mohammadi, & Raahemifar, 2014; Zhuming, Li Da, & Chengen, 2014). Although many studies have proposed solutions for decision making and energy optimisation in the residential sector of the SG (Anees & Chen, 2016; Rathnayaka, Potdar, Dillon, & Kuruppu, 2015; Sianaki & Masoum, 2013b), energy-efficient manufacturing is more complicated since efficacy and efficiency are priorities in all layers of operational management (Bunse, Vodicka, Schönsleben, Brülhart, & Ernst, 2011; Karlsson, 2011) (Hasanbeigi, Menke, & du Pont, 2010; Sandberg & Söderström, 2003). Industrial participants in a DRP need to assess the risks associated with DRP engagement in terms of financial gain and loss. For this reason, the aim of this paper is to address the following questions:

1. Which methodology is able to assess the effects of DRP engagement on operational management in order to minimise the risks of participation in a DRP?
2. How can participation in a DRP impact the functional factors of operational management such as materials, methods, supply chain management, agility, and machine operation?
3. How can different departments of an organisation work together to coordinate the local sensing of the risks posed by DRP participation?
4. If an energy/operation manager decides to curtail the energy being supplied to their equipment, which equipment will have priority?
5. How do we identify which equipment with a deferrable load can be shifted to the non-peak period?
6. How do we construct an optimisation model to reflect the operational risk factors in energy planning?
7. In light of the aforementioned strategies, which strategy should we choose? Should it be on-site generation, accepting a DRP, or rejecting a DRP and accepting the high cost of electricity energy?

The proposed methodology for the first question is explained in Section 4.1. The solutions for questions two and three are discussed in section 4.2. Sections 5 and 6.2 describe the proposed methodologies for the fourth and fifth questions, and finally the solutions for questions six and seven are presented in sections 6 and 7.

The paper's innovation and contribution is as follows:

- The methodology of this paper uses the TOPSIS method as a decision-making tool with a linear programming model. For the simulation of the algorithm, two robust types of software are employed, namely MATLAB software and IBM ILOG CPLEX Optimizations Studio to simulate a decision-making matrix of size of 10 to 26 for discrete time planning in 24 hours.

- Using the proposed methodology, the managerial and operational factors will be revealed and considered in decision-making about a DRP.
- By utilising real-time energy consumption information, an energy optimisation method is employed to schedule and allocate energy during a DRP to identify any potential loss of production.
- Energy managers are able to make decisions about whether or not to engage in a DRP after considering the DRP's energy constraints and the potential loss of production whilst achieving the optimised level of energy.

The remainder of this paper is organised as follows. Section 2 presents a theoretical framework and outline of the paper. Section 3 presents the related work. In section 4, the Delphi method is proposed to determine the appropriate criteria for assessing the effects of DRP engagement. Section 5 presents the TOPSIS method with information entropy to utilise the criteria to assess which equipment needs load curtailment during a DRP. In section 6, energy, power and cost correlations are delineated and a linear programming (LP) mathematical model for energy optimisation and a DRP engagement evaluation algorithm are presented. Section 7 presents a case study simulating the proposed methodologies. Section 8 presents the sensitivity analysis of the proposed algorithm and section 9 concludes this paper.

2. Theoretical framework and paper outline

The overall structure of the proposed methodology is shown in Fig.1. The figure details the three identified problems and the methodologies proposed for solving them. The first problem is to identify the criteria by which the direct effects of limiting or decreasing energy consumption on the production rate can be assessed. As different industries have different processes and procedures, an effective decision-making tool is required to obtain consensus among the experts about which criteria to use to assess the effects of a DRP on operations management. In this paper, we address this issue using the Delphi method which is the first step of our methodology as discussed in sections 4.1 and 4.2.

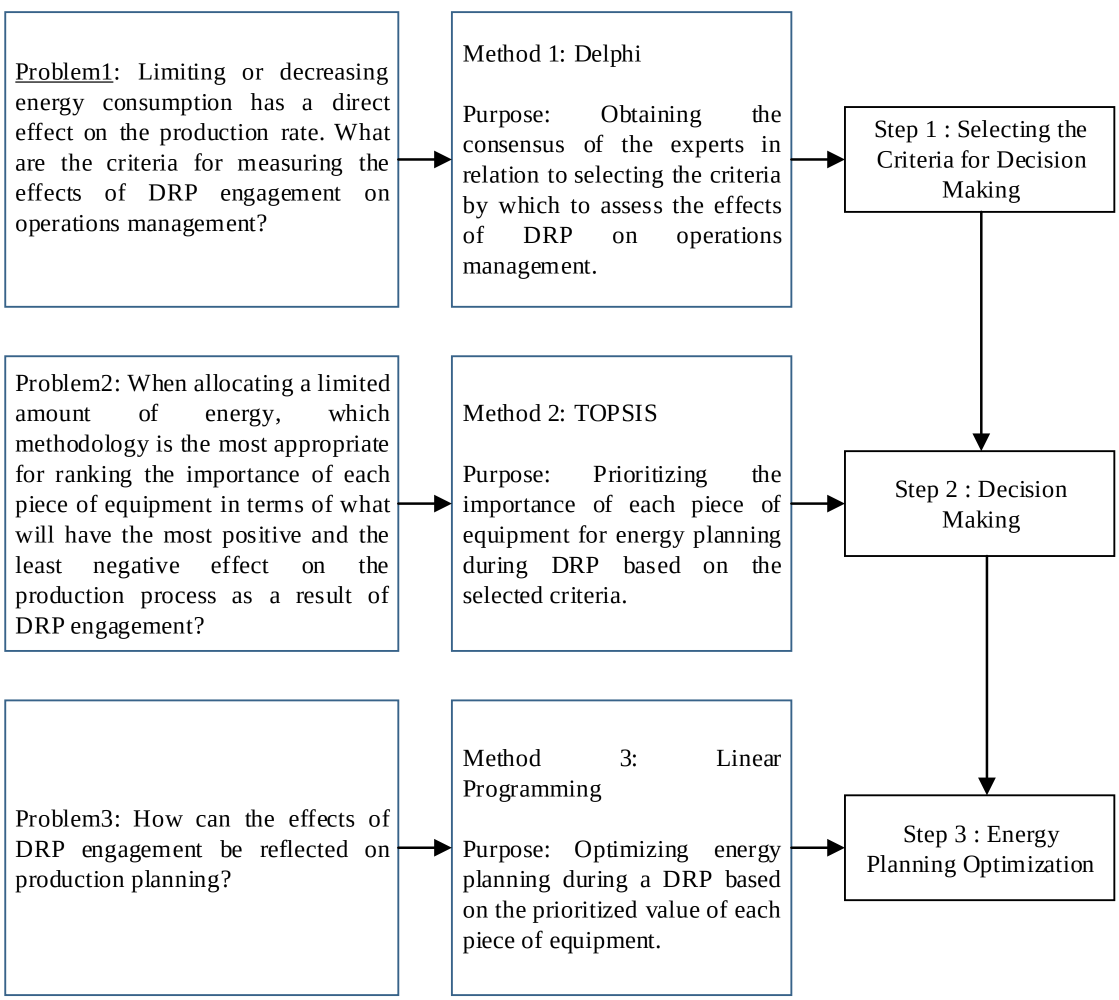

Fig. 1. The proposed methodology

The second problem is to rank the importance of each piece of equipment in terms of what will have the most positive and the least negative effect on the production process as a result of DRP engagement. To do this, the TOPSIS methodology is used to prioritise the importance of each piece of equipment for energy planning during a DRP based on the selected criteria. This methodology is described in section 5. The third problem is to analyse the effects of DRP engagement on production planning. To do this, a linear programming model is utilised for equipment energy planning based on the DRP's energy limitations, production restrictions, and the calculated prioritised value of each piece of equipment. This methodology is discussed in sections 6.1 to 6.3.

3. Related studies and identified problems

This review aims firstly to demonstrate the significance of the topic by providing readers with an overview of the DSM literature in the context of electricity energy management in the industrial sector of the SG, and secondly to support the proposed methodology by comparing the related studies.

The new technologies in the electrical market and power system operations transformed DSM concepts and theory, leading to the development of a new theoretical framework for DSM, as discussed by Meyabadi & Deihimi (2017). The authors reviewed many different types of DSMs, finding that the expedient engagement of customers is at the core of all these programs. Therefore, customers, specifically in the industrial and manufacturing sectors, need the mechanisms and decision support models to adjust their operations based on the amount of energy consumption committed to in the DRP contract. This is referred to as energy-efficient manufacturing. The literature review conducted by Biel & Glock (2016) found that energy-efficient manufacturing aims to reduce energy consumption by two types of research, technological advancements in the production processes and adjusting the managerial parameters of the production process. The aim of the latter is to develop a production plan taking into consideration the energy-related objectives and constraints such as the minimisation of energy consumption, energy cost, energy-related greenhouse gas emissions, and compliance with the maximum contracted power demand. Biel and Glock (2016) found that there is no existing research which offers assistance to industrial customers when they are in the process of deciding to accept or reject a DRP. Similarly, the importance of encouraging industrial customers to engage in market participation has been demonstrated comprehensively by Shoreh, Siano, Shafie-khah, Loia & Catalão (2016) and Sharifi, Fathi & Vahidinasab (2017).

A recent study of the literature on energy-efficient scheduling in manufacturing companies (Gahm, Denz, Dirr, & Tuma, 2016) revealed that a broad understanding of the scheduling-based energy characteristics of the involved manufacturing systems and their corresponding interdependencies are essential for enhancing energy efficiency in production planning. Energy management in industrial units with the emergence of the SG and DRPs in the industrial sector has attracted intense research interest. More recently, a discrete manufacturing production model and automated real-time demand biding algorithm was presented by Li & Hong (2017). The authors formulated a mixed integer programming optimisation model to maximise a manufacturer's profit. The main difference between their work and the work in this paper is that Li and Hong propose an incentive-based DRP. Li and Hong admit that a price-based DRP for industrial consumers can result in load reduction which will inevitably result in a financial loss. Resolving this issue is one of the objectives of our proposed algorithm. Moreover, distributed energy resources are not considered in Li & Hong's algorithm. A similar study conducted by Wang, El-Farra & Palazoglu (2017) considered a hybrid renewable energy resource in their optimal model.

Manufacturing scheduling of multiple factories was studied by Zhang, Zhao, & Sutherland, (2015) to explore the potential for electricity cost reduction under real-time pricing. Critical Peak Pricing (CCP) and Time of Use for manufacturing enterprises was compared by Wang & Li (2016), the study showing that an average industrial customer with production flexibility and with the proper rescheduling of electricity use can save 30.45% on their annual electric bill by engaging in CPP.

The significance of prioritising loads and products is discussed by Mohagheghi & Raji (2014), who divide products into three categories, A, B, and C, from the highest to the lowest to prioritise workstations for load curtailment in a DRP. Daily production and inventory constraints, maintenance schedules, crew management, and the characteristics of each workstation are considered in the conceptual model which is designed to assess the processes of load curtailment or temporary shut-down. However, after ranking the workstations, Mohagheghi & Raji (2014) did not propose a methodology to determine the electricity cost-saving potential or a method to evaluate whether or not the financial benefits of a DRP are attractive for incentives.

A load scheduling strategy aimed at minimising the electricity costs of industrial users in a real-time pricing DRP is presented by Roos & Lane, (1998). This research utilises a linear programming optimisation algorithm to minimise electricity costs by harmonising the hourly marginal rate duration curve with maximum and minimum power demand levels. Electricity costs for the end-user with and without the load scheduling operation were modelled, taking into consideration the total spare energy consumption capacity and optimum load scheduling. However, the potential electricity cost savings and the cost of unserved energy was not considered to evaluate the economic value of RTP.

The effect of unreliable and finite information on the efficiency of operational plans in a RTP scheme of a DRP was investigated by Karwan & Keblis (2007) and the LP mathematical model was utilised to minimise the average hourly operating cost under the

RTP scheme. Bego, Li & Sun (2014), Sun & Li (2014), Sun, Li, Fernandez & Wang (2014) and Wang & Li (2013) focused on the throughput of sustainable manufacturing systems in different DRP schemes, such as CPP, RTP and TOU. These authors mostly employed mixed integer nonlinear programming methods to achieve near-optimal solutions to minimise energy costs by concentrating on reservation and buffer inventory management build-up during off-peak periods to overcome load curtailment. However, these methodologies give rise to problems when there is a large variety of products in the system and production flexibility is not responsive enough to build a buffer. Furthermore, production and lean manufacturing paradigms, such as just-in-time and pull production, are in contrast with these proposed methodologies. In addition, these methods are not suitable for perishable products such as food.

On the other hand, one of the aims of the SG is the development of distributed energy resources. The research of Ding, Hong & Li (2014) focuses on this aspect of the SG and analyses the cost of purchasing and generating electricity against the revenue generated by selling electricity to the grid. The authors established an LP model to minimise the total energy costs in an hourly day-ahead DRP. Furthermore, the tasks are divided into schedulable and non-schedulable groups, making the research methodology more feasible to implement. This research deals with the flow of electricity together with other resources including the flow of materials, real-time processes, and the serious financial and technical problems posed by a reduction in electricity.

The attention of the aforementioned research projects is mainly focused on energy management by minimising energy costs while considering production constraints, machine operations and maintenance, and inventory management to make throughputs as efficient as possible by utilising linear and non-linear programming models. But to the best of the authors' knowledge, no research has yet focused on evaluating the feasibility of a DRP in terms of supporting operations managers to make decisions about DRP adoption. The existing research could be useful when manufacturers decide to participate in a DRP; however, prior to making this decision, they need to investigate the potential gains and losses associated with doing so. Furthermore, the associated risk of energy loss is not limited to production management; it is an energy efficiency and productivity matter. As mentioned, ICT can help to manage and reduce energy consumption and emissions in manufacturing processes. ICT in manufacturing industries comprises different systems such as enterprise resource planning (ERP), customer relationship management (CRM), manufacturing execution system (MES), material resource planning (MRP), and product lifecycle management (LCM) (Bunse et al., 2011). For example, implementing the Internet-of-Things (IOT) in the industrial sector can facilitate the real-time intelligent collection of data on the energy consumption of a product over its entirety (Tao, Zuo, Xu, Lv, & Zhang, 2014) and can assist numerous types of decision-making at different levels of enterprise systems (Zhuming et al., 2014).

Fig. 2 shows an Energy Management System (EMS) which has been combined with an ERP system to form an industrial DR information model. Our proposed methodology in this model is embedded in EMS to evaluate the effects of a DRP on operations and production management. Energy information such as price signals is sent through the wide area network (WAN) to the organisation while the energy consumption information received by the EMS with the local area network (LAN) is sent back to the utility by the smart meter. The decision-making algorithm for this expert system is explained in the following sections.

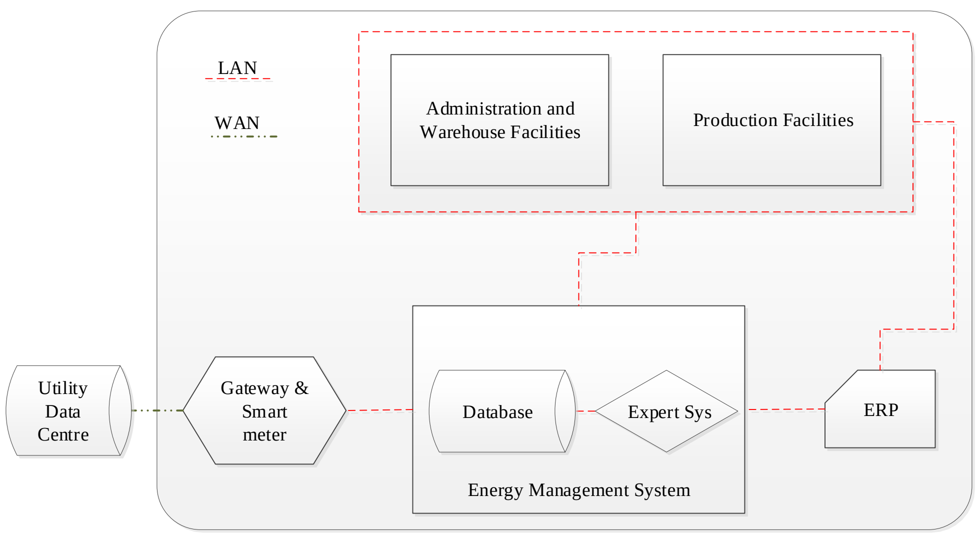

Fig. 2. Industrial DR information model

4. Decision making to evaluate equipment operation and energy management

The overall structure of the proposed methodology is shown in Fig.1. The first step is to select the criteria for decision making. Prior to explaining this, we review the literature relating to the application of multi-criteria decision making (MCDM) in energy management.

4.1. MCDM for energy planning: an introduction

MCDM techniques have increasingly been employed for energy planning decisions. These methods can be classified as a) value measurement models, b) goal and reference models and c) outranking models (Løken, 2007). Of the numerous MCDM methods, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), originally presented by Hwang & Yoon (1981), has received great interest from researchers as an effective tool for evaluating and selecting the energy system performance (Behzadian, Khanmohammadi Otaghsara, Yazdani, & Ignatius, 2012). For instance, Aalami, Moghaddam & Yousefi (2010) developed an extended responsive load economic model based on price elasticity and customer benefit function, and the prioritisation of DRPs was realised by means of the TOPSIS method. Xiaodong, Limin & Changqin (2011) evaluated the effectiveness of the SG using fuzzy TOPSIS methods. Sianaki & Masoum (2013a) implemented the fuzzy TOPSIS approach to allocate energy flow to a building during a DRP.

TOPSIS is a practical method for ranking and selecting many possible alternatives by measuring *Euclidean distances*. The working principle of TOPSIS is based on the fact that the selected alternative should have the shortest distance from the positive ideal solution (PIS) and be the farthest from the negative ideal solution (NIS). In fuzzy TOPSIS, this distance is based on fuzzy positive and negative ideal solutions. We chose TOPSIS from the different methodologies because we will use these distances in our optimisation methodology presented in section 7.3.

The first step in all decision-making methods is determining the criteria. The principles and methods for selecting the appropriate criteria in decision-making for energy planning are presented in (Wang, Jing, Zhang & Zhao, 2009). To select the criteria, the energy expert should follow systemic, consistency, independency, measurability, and comparability principles. There are four main methods for selecting criteria, namely Delphi, least mean square (LMS), correlation coefficient method, and min-max deviation (Wang et al., 2009).

The Delphi method is employed in our proposed methodology because it engages all the experts from different departments of an organisation to work together to coordinate the local sensing of the risks and interruptions posed by DRP participation. This method is able to appropriately and relevantly answer the second and third research questions detailed in the introduction. This method is explained in the following section.

4.2. Selecting decision-making criteria for energy planning using the Delphi method

As discussed in the introduction, offering commercial incentives or shifting production to off-peak periods can cause a dilemma since a DRP may disrupt the production process and the organisation may incur production losses if its energy load is decreased. Therefore, deciding to participate in a DRP needs investigation in the more rooted layers of organisational operations.

In order to identify which organisational and operational factors will be affected by DRP engagement, we conducted a literature survey on Total Quality Management (TQM) and lean-agile manufacturing to categorise these factors (Gurumurthy & Kodali, 2008; Naylor, Naim, & Berry, 1999). Accordingly, ten factors were initially identified, namely materials, methods, management, marketing, supply chain management and agility, machines, measurements, financial management, human resource management, and environment. We limited our study to these ten factors because these are seen to be the most significant and are common to all the research reviewed. Our review aimed to answer the question of how engaging in a DRP can affect these factors. For example, if participating in a DRP leads to production curtailment, then human resources need to be balanced or it may lead to job dissatisfaction as employees may be forced to work fewer hours or may face changes to their rosters. Participating in a DRP can also impact marketing, as it affects customer satisfaction through delays in delivery time. Engaging in a DRP and changing the production plan means changing the machine operating schedule or machine working status which may decrease the efficiency of the machine and increase its need for recalibration. So, a study of the effects of DRP engagement on each factor is complex. For this reason, we implement the Delphi method to solve this problem.

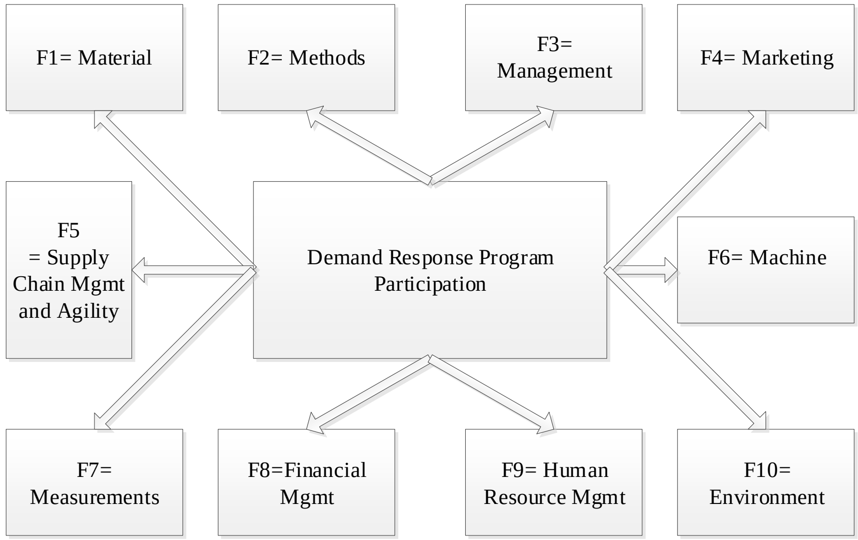

Fig. 3. The factors affected by DRP participation

The Delphi method is employed to select the most appropriate criteria to evaluate the effects of DRP participation on these factors and energy planning.

The Delphi technique is a systematic procedure to use with a panel of experts to arrive at a consensus of opinion about future events or to assist decision making in different disciplines (Wang et al., 2009). Applications of the Delphi method were studied by Rowe & Wright (1999) and Galo, Macedo, Almeida & Lima (2014) employed this method to select criteria from many variables to evaluate electrical systems in the SG.
Following the Delphi method, a panel of experts from different organisational departments with different expertise is formed to forecast how the factors in Fig.3 will be affected by implementing a DRP. The experts are required to complete a questionnaire to ascertain their opinions on the risks associated with a DRP and to arrive at consensus.

The flowchart depicted in Fig.4 is proposed for implementing the Delphi method considering the following details (Rowe & Wright, 1999):

a) The four key features of the Delphi procedure comprise anonymity (step 1), iteration (steps 2, 3 and 4), controlled feedback (steps 4 to 2), and statistical aggregation of group responses (step 5).
b) The Delphi panel size is modest and a group of 10 to 18 members is recommended.
c) The experts belong to the production, quality, engineering, logistics, financial, and sales departments.
d) The first round of the Delphi procedure is unstructured and the number of criteria may decrease in further rounds.
e) Experts may use their own internal documents, expertise, and knowledge to assess the effects of a DRP on their operations.
f) Greater consensus between the experts is determined by a reduction of variance in responses.

We explain these steps when discussing our computational experiment in Section 7.1.

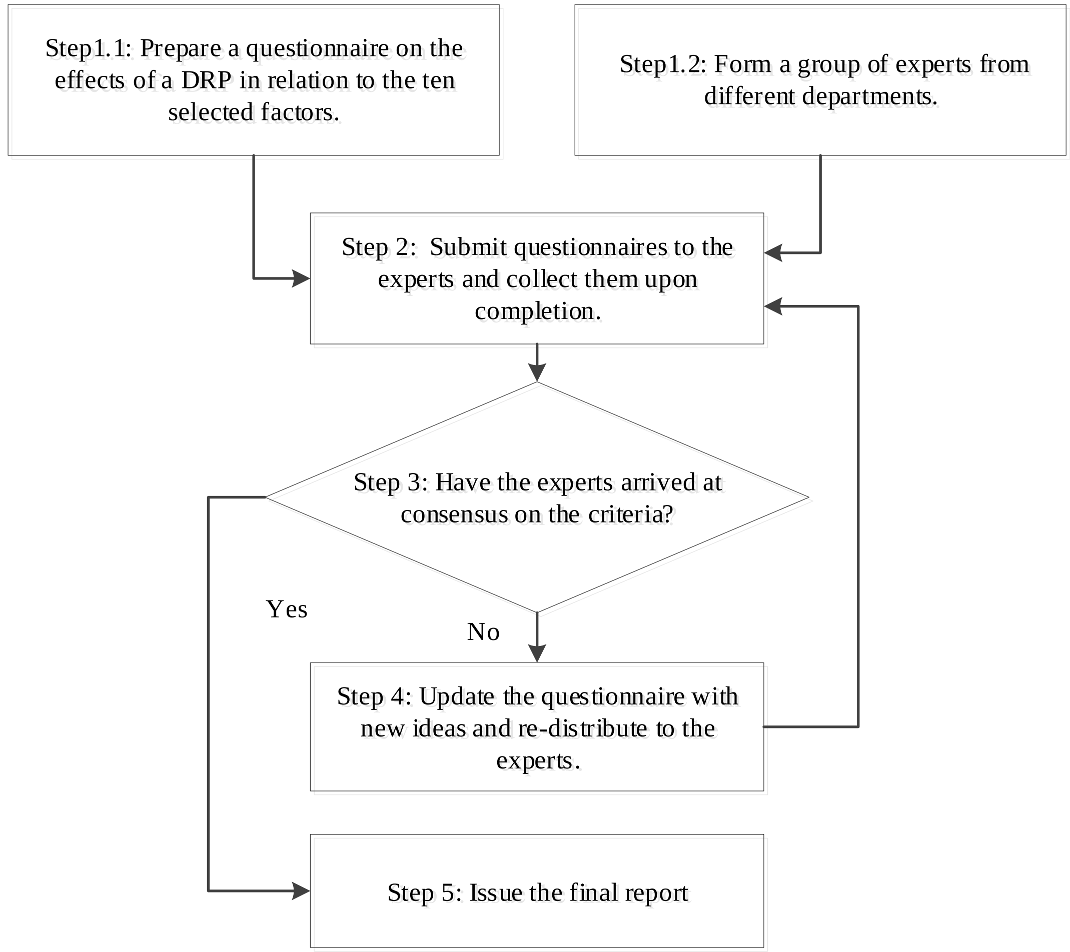

Fig.4. Delphi procedure for selecting criteria

4.3. The proposed decision-making methodology

After arriving at general consensus on the decision-making criteria, the TOPSIS method is employed to prioritise the importance of each piece of equipment for energy planning during a DRP in relation to the criteria. Later, we use these values in an optimisation model to allocate energy to the equipment accordingly. Using the TOPSIS methodology, we aggregate the experts' knowledge for risk mitigation purposes when an organisation decides to participate in a DRP.

5. TOPSIS method: a decision support tool

The TOPSIS method (Behzadian et al., 2012) based on information entropy is proposed as a decision support tool for an energy manager to determine the effects of a DRP on productivity and energy efficiency. In decision science, two terms are used, *alternatives* and *criteria*. Alternatives are selected, sorted, or prioritised based on criteria. In this section, we use the term *alternatives* to refer to all the equipment and the term *criteria* to refer to the criteria determined in the previous section. In the TOPSIS method, there are two types of criteria. Positive criteria are those that should be increased and negative criteria are those which need to be decreased in order to mitigate risk. The purpose of this methodology is to first arrive at an ideal solution and a negative ideal solution, and then find a scenario which is nearest to the ideal solution and farthest from the negative ideal solution. This methodology can be implemented by taking the following steps:

Step 1: *Specify alternatives and criteria* for the equipment to which the energy must be allocated. This step is explained in the previous section. Assume that there are m possible pieces of equipment called $A = \{A_1, \dots, A_m\}$ which are to be evaluated against c criteria $C = \{C_1, \dots, C_c\}$.

Step 2: *Assign ratings to criteria and alternatives* using matrix X presented in Eq.1 where x_{ig} indicates the value of alternative A_i for criterion C_g:

$$X_{m\times c} = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & C_g & C_c \end{array} \\ \begin{array}{c} A_1 \\ A_i \\ \vdots \\ A_m \end{array} & \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1c} \\ . & . & x_{ig} & . \\ \vdots & \vdots & \cdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mc} \end{bmatrix} \end{array} \quad (1)$$

Step 3: *Calculate the weight of criteria using the entropy technique* to normalise the decision matrix Eq.1 using formula Eq.2:

$$q_{ig} = \frac{x_{ig}}{(x_{1g}+\cdots+x_{mg})} \; ; \qquad \forall g \in \{1,..,c\}. \quad (2)$$

The information entropy of criterion g is given by definition of information entropy presented in Eq.3:

$$\Delta_g = -k \sum_{i=1}^{m} q_{ig} \,.\ln q_{ig} \; ; \; \forall g \in \{1,..,c\} \quad (3)$$

where $0 \leq \Delta_g \leq 1$ can be ensured with the coefficient k, through $k = 1/ln(m)$. Generally, an index with a bigger information entropy Δ_g has greater variation (Shannon, 2001).Therefore, the weight through deviation degree d_g can be computed by (Eq.4):

$$d_g = 1 - \Delta_g \, , \qquad (g = 1, \dots, c). \quad (4)$$

Finally, the weight for the criteria using the entropy technique can be calculated as follows:

$$w_g = \frac{d_g}{(d_1+\cdots+d_c)} \quad (5)$$

Eqs. 6 and 7 are used to aggregate the energy manager's weight vector λ_g and obtain the aggregated weight w'_g:

$$w'_g = \frac{\lambda_g.w_g}{(\lambda_1.w_1+\cdots+\lambda_c.w_c)} \quad (6); \quad w' = \{w'_1, w'_2, \dots, w'_c\} \quad (7)$$

Step 4: *Construct a normalised decision matrix* using the vector normalisation method, calculate normalised value r_{ig} by (Eq.8) and construct matrix $N_{m\times c}$ presented by (Eq.9):

$$r_{ig} = \frac{x_{ig}}{\sqrt{(x_{1g}^2+\cdots+x_{mg}^2)}} \quad (8)$$

$$N_{m\times c} = [r_{ig}]_{m\times c} \, , \qquad (i = 1, \dots, m \, ; g = 1, \dots, c). \quad (9)$$

Step 5: *Construct the weighted normalised decision matrix* by building the diagonal matrix $w'_{c\times c}$ with element w'_g in (Eq.6) to reach the V matrix:

$$V = N_{m\times c}.w'_{c\times c} = (v_{ig})_{m\times c} \quad (10)$$
$$(i = 1, \dots, m \, ; \; g = 1, \dots, c).$$

Step 6: *Compute the positive ideal solution (PIS)* A^+ *and the negative ideal solution (NIS)* A^- of the alternatives:

$$A^+ = \left\{\left(\max v_{ig} \,|g \in G\right); \left(\min v_{ig} |\; g \in G'\right)\right\} = ({v_1}^+, {v_2}^+, \dots, {v_c}^+) \quad (11)$$

$$A^- = \left\{\left(\min v_{ig} \,|g \in G\right); \left(\max v_{ig} |\; g \in G'\right)\right\} = ({v_1}^-, {v_2}^-, \dots, {v_c}^-). \quad (12)$$

where G and G' are the subsets of positive and negative criteria, respectively.

Step 7: *Compute the distance of each alternative from PIS (${d_i}^+$) and NIS (${d_i}^-$):*

$${d_i}^+ = \sqrt{\sum_{g=1}^{c}\left(v_{ig} - v_g^+\right)^2} \quad (13)$$

$${d_i}^- = \sqrt{\sum_{g=1}^{c}\left(v_{ig} - v_g^-\right)^2} \quad (14)$$

Step 8: *Compute the closeness coefficient of each alternative:*

$$CC_i{}^+ = \frac{{d_i}^-}{({d_i}^- + {d_i}^+)} \quad ; \quad i = 1, 2, \dots, m \quad (15)$$

Step 9: *Rank the alternatives:*

$$v = \left\{ v_i \middle| \max_{1 \le i \le m} (CC_i{}^{+}) \right\} \quad (16)$$

The final step takes us to the ranking of the equipment. This ranking indicates that the equipment with a higher value should be kept in production during a DRP and any load curtailment for this equipment will constitute a high risk to the enterprise. Therefore, it is preferable to curtail the energy of the equipment with a lower ranking. As explained in section 4.1, we utilise these values in our optimisation methodology as proposed in the next section.

6. Energy consumption optimisation

6.1. Energy, cost and power correlation

For energy and its associated cost formulation, it is assumed that E_{ij}^{1} denotes the energy demanded by equipment i in timeslot j with energy price U_j^1 where the associated energy cost C_{ij}^1 can be calculated as (Roos & Lane, 1998), $C_{ij}^1 = U_j^1 \times E_{ij}^1$. Therefore, if the consumer allocates the same budget to timeslot j in which $EC_j^2 = EC_j^1$ then the change in energy level contrasts with the same proportion in which the energy price has been increased as shown by (Eq.17).

Assume $C_{ij}^1 = U_j^1 \times E_{ij}^1$ and $C_{ij}^2 = U_j^2 \times E_{ij}^2$ if $C_{ij}^2 = C_{ij}^1$ then $(U_j^2 \times E_{ij}^2) = (U_j^1 \times E_{ij}^1)$ or $\frac{E_{ij}^2}{E_{ij}^1} = \frac{U_j^1}{U_j^2}$ (17)

Here, we divide the DRP duration by n number of timeslots, to reach the unit of time for energy planning as follows:

$$\frac{\text{Duration of DRP}}{\text{number of timeslots (n)}} = \mathrm{T} \quad (18)$$

where T is the time unit of planning and it is a constant and independent parameter to any timeslot and equipment; so, it does not have any subscript or index in the formula. Hence, the allocated operation time, energy and power are limited by this constraint. The above correlation between power, time, and energy will be used as constraints in the proposed optimisation model discussed in the next section (Eq.35).

Total energy and cost of m number of electrical equipment $E_{total\ m}^{n}$ and $C_{total\ m}^{n}$, during n number of timeslots can be formulated by Eq.19 and Eq.20. It is assumed that the energy price in each timeslot is constant and each timeslot is considered as a time unit of planning.

$$E_{total,m}^{n} = \sum_{j=1}^{n} \sum_{i=1}^{m} E_{ij} = \sum_{j=1}^{n} \sum_{i=1}^{m} (P_{ij} \times t_{ij}) \quad (19)$$

$$C_{total,m}^{n} = \sum_{j=1}^{n} \sum_{i=1}^{m} (P_{ij} \times t_{ij}) \times U_j \quad (20)$$

$$i = 1,2,3,..,m\,; \quad j = 1,2,3,..,n \quad (21)$$

$$t_{ij} \le \mathrm{T} \quad (22)$$

where E_{ij} and P_{ij} are the amount of energy and power demanded by equipment i during timeslot j for executing an operation which takes t_{ij} in each T; and, U_j is the price of energy in timeslot j that is fixed during timeslot j. The product quantity produced can be related to its electricity consumption. This relationship is the product quantity function of electricity consumption shown by Eq.23 and 24 (Hu & Hu, 2013).

$$Q_{ij} = f_{Q_i}(E_{ij}) \quad (23); \qquad AQ_{ij} = \frac{Q_{ij}}{E_{ij}} \quad (24)$$

where Q_{ij} is the production rate of equipment i by consuming energy E_{ij}, and AQ_{ij} is the average production rate for each unit of energy ($number\ of\ products/kW.h$). This formula is used to compute the production loss derived by energy curtailment (Table 2).

6.2. DRP engagement evaluation: Equipment with deferrable (L_D) and non-deferrable (L_{ND}) loads

To evaluate DRP engagement, the load of each piece of electrical equipment can be classified as either interruptible or non-interruptible. Furthermore, interruptible loads can be categorised as either deferrable (L_D) or non-deferrable (L_{ND}) loads. Equipment categorised as (L_D) and (L_{ND}) can be recognized as follows:

- The equipment classified as L_D can run and be scheduled at any time and in a timeslot, as their operation is not a prerequisite to the other processes in the flow process chart.
- The equipment classified as L_D is interruptible.

- These types of loads will not disrupt the other processes and should not cause a delay in operation management.
- Conversely, equipment classified as L_{ND} is for unscheduled operations for DRP because due to their load scheduling, the industrial unit will face financial damage or other processes will be interrupted.

Operations in chemical production such as an oil refinery, plating process, and heat treatment by a furnace are in the L_{ND} category. These types of loads cannot be scheduled for DRP engagement (Ding et al., 2014). Operations such as metal forming, stamping and cuttings in a workshop press or spring manufacturing are examples of the L_D category. In this paper, the proposed methodology focuses on L_D; therefore, $E^n_{total,m}$ in Eq.19 can be formulated as:

$$E^n_{total,m} = E^n_{total,m_{ND}} + E^n_{total,m_D} \tag{25}$$

$$C^n_{total,m} = C^n_{total,m_{ND}} + C^n_{total,m_D} \tag{26}$$

$$E^n_{obj,m_D} = E^n_{total,m_D} - (E^n_{total,m} - E^n_{DR,m}),\text{ or} \tag{27}$$

$$E^n_{obj,m_D} = E^n_{DR,m} - E^n_{total,m_{ND}} \tag{28}$$

$$C^n_{obj,m_D} = \sum_{i=1}^{m_D} E^n_{obj,i,j} \times U_j; \quad \forall \text{j} \in \{1,..,\text{n}\} \tag{29}$$

where $E^n_{total,ND}$ and $E^n_{total,D}$ are the total energy of the equipment with the non-deferrable and deferrable loads and their associated costs are $C^n_{total,ND}$ and $C^n_{total,D}$, respectively. m_{ND} and m_D are the number of pieces of equipment with non-deferrable and deferrable loads, respectively. By participating in demand response and accepting DR regulations and energy price U_j, the level of total required energy $E^n_{total,m}$ will be curtailed to reach the demand response level $E^n_{DR,m}$. As discussed above, this excessive amount is subtracted from deferrable energy level E^n_{total,m_D}. This situation constructs the objective level of energy E^n_{obj,m_D} which is calculated by Eq.27 or Eq.28. This limit of energy and its associated cost, C^n_{obj,m_D} in each timeslot are the constraints in our optimisation model. $E^n_{total,m}$ is the level of energy that is required based on the production plan. These levels of energy for our case study are shown in Fig. 10. In the proposed methodology, it is assumed that if $E^n_{DR,m} < E^n_{total,m_{ND}}$, the DRP will interrupt the total production process and engagement is not feasible. We present a DRP engagement evaluation algorithm following the optimization method given in the next section.

6.3. Mathematical optimisation model and DRP engagement evaluation algorithm

In this section, a linear programming model is presented to perform energy optimisation and energy assignment for a DRP. We design the optimisation function by maximisation because of the positive and direct correlation between production and electricity consumption (Hu & Hu, 2013). Hence, the more products that are produced, the more energy is consumed. Therefore, we include the aforementioned DRP constraints in the formula and aim to maximise the production to simulate a DRP as shown in the objective function by (30). The scheduling time horizon is divided into n timeslots to plan the energy for m_D amount of equipment and "i" is an index to present the equipment with deferrable loads. Considering energy price U_j in timeslot j, the energy cost of each "i" will be computed. Constraints 32 and 33 will not allow these amounts to increase.

A DRP imposes two constraints that are considered as inputs to our model. The first constraint is the amount of total energy allocated to each timeslot that is shown by δ_j in Eq.33 (calculated by Eq.28) such that the total energy of equipment E_{ij} in that timeslot will not exceed this value (constraint 34). The second constraint is energy price U_j, where constraint 34 indicates that the cost of total equipment during timeslot j will not exceed the total cost allocated to that timeslot (Υ_j). In the presented model, it is assumed that the energy price in each timeslot is constant and the equipment's load is deferrable. In the previous section, subscript "i" is used to indicate the amount of total equipment "m" but to avoid confusion in the following mathematical model, we use this subscript for the equipment with deferrable loads "m_D".

$$\text{Maximise } \sum_{i=1}^{m_D} \sum_{j=1}^{n} v_i E_{ij} \tag{30}$$

Subject to:

$$\sum_{j=1}^{n} E_{ij} \le e_i, \quad \forall \text{i} \in \{1,..,m_D\} \tag{31}$$

$$\sum_{j=1}^{n} E_{ij}.U_j \le c_i, \quad \forall \text{i} \in \{1,..,m_D\} \tag{32}$$

$\sum_{i=1}^{m_D} E_{ij} \leq \delta_j , \qquad \forall j \in \{1,..,n\}$ (33)

$\sum_{i=1}^{m_D} E_{ij}.U_j \leq \Upsilon_j , \ \forall j \in \{1,..,n\}$ (34)

$E_{ij} \leq \mathrm{T} \times p_i \ , \qquad \forall i \in \{1,..,m_D\}, \forall j \in \{1,..,n\}$ (35)

$e_i, \ p_i, c_i \ , U_j \geq 0$ (36)

$i \in \{1,..,m_D\} \ ; j \in \{1,..,n\}$ (37)

where the indices, parameters and decision variables are explained as follows:
Indices:

$i \in \{1,..,m_D\}$ Index of equipment with deferrable load
$j \in \{1,..,n\}$ Index of timeslot
Parameters:
e_i : Total energy allocated to equipment i during n timeslot
c_i : Total energy cost allocated to equipment i
p_i : Amount of power used by equipment i
v_i : Value of importance belongs to equipment i
U_j: Price of energy in timeslot j indicated by DRP
δ_j : Total energy allocated to timeslot j
Υ_j : Total cost of energy allocated to timeslot j
T : Time unit of planning
m_D: amount of equipment with deferrable loads
n : Number of timeslots
and the decision variable is:
E_{ij} : Amount of energy allocated to equipment i in timeslot j

Equipment	TOPSIS Value, Power	t_1	$t_2, t_3, \ldots, t_{j-1}$	t_j	$t_{j+1}, \ldots, t_{n-1}$	t_n	$\sum$ Discrete scheduling time horizon
1	v_1, p_1	U_1, E_{11} $E_{11} \leq \mathrm{T} \times p_1$		U_j, E_{1j} $E_{1j} \leq \mathrm{T} \times p_1$		U_n, E_{1n} $E_{1n} \leq \mathrm{T} \times p_1$	$\sum_{j=1}^{n} E_{1j} \leq e_1$, $\sum_{j=1}^{n} E_{1j}.U_j \leq c_1$
2 3 …	v_2, p_2 v_3, p_3 …						
i	v_i, p_i	U_1, E_{i1} $E_{i1} \leq \mathrm{T} \times p_i$		U_j, E_{ij} $E_{ij} \leq \mathrm{T} \times p_i$		U_n, E_{in} $E_{in} \leq \mathrm{T} \times p_i$	$\sum_{j=1}^{n} E_{ij} \leq e_i$, $\sum_{j=1}^{n} E_{ij}.U_j \leq c_i$
…	…						
m_D	v_{m_D}, p_{m_D}	$U_1, E_{m_D 1}$ $E_{m_D 1} \leq \mathrm{T} \times p_{m_D}$		$U_j, E_{m_D j}$ $E_{m_D j} \leq \mathrm{T} \times p_{m_D}$		$U_n, E_{m_D n}$ $E_{m_D n} \leq \mathrm{T} \times p_{m_D}$	$\sum_{j=1}^{n} E_{m_D j} \leq e_{m_D}$, $\sum_{j=1}^{n} E_{m_D j}.U_j \leq c_{m_D}$
$\sum$		$\sum_{i=1}^{m_D} E_{i1} \leq \delta_1$, $\sum_{i=1}^{m_D} E_{i1}.U_1 \leq \Upsilon_1$		$\sum_{i=1}^{m_D} E_{ij} \leq \delta_j$, $\sum_{i=1}^{m_D} E_{ij}.U_j \leq \Upsilon_j$		$\sum_{i=1}^{m_D} E_{in} \leq \delta_n$, $\sum_{i=1}^{m_D} E_{in}.U_j \leq \Upsilon_n$	$max \sum_{i=1}^{m_D} \sum_{j=1}^{n} v_i E_{ij}$

$i \in \{1,..,m_D\}$ Index of equipment,
$j \in \{1,..,n\}$ Index of timeslot

Fig. 5. Energy assignment with constraints

The objective function maximises the use of energy for the equipment in each timeslot along discrete time horizon energy planning, taking into account the value of each piece of equipment (v_i) calculated using the TOPSIS approach. Here we utilised the Euclidean metric property of the closeness coefficient (CC_i^{+}, (15)) in the formula.

The above optimisation model resembles the Multiple Knapsack Problem (MKP) but it is not, as the decision variable is not binary. Instead, the model benefits from the Cargo Problem. Assume that there is an aeroplane that has a specific total weight profile and must carry many parcels. For instance, you cannot put the heavy items in the bottom of aeroplane and the light ones in front. These parcels have different volumes and weights and the problem is how to fit them into the aeroplane to carry as many parcels as possible. In our problem, the planning time horizon during a DRP is like the aeroplane as it has a specific energy profile and the equipment is like the parcels. The volume and weight of each parcel is similar to the amount of energy and the cost of each piece of equipment required to produce a unit of product (Q_{ij}, (23)). This scenario is shown in Fig.5. This figure shows the equipment versus the discrete scheduling time horizon in a DRP where the two-dimension boundaries are depicted clearly. Furthermore, the figure shows the complexity of the optimisation model.

In the above mathematical model, Eq.31 shows the constraint of the energy allocation limit to equipment i during time horizon planning while Eq.32 indicates its associated cost constraint. Any change to this cost limit will be projected to the product cost and profit. Eq.33 is the constraint of energy in each timeslot indicating that the sum of the consumed energy during each timeslot should not exceed the allocated energy level dedicated to that timeslot. Eq.34 is associated with the cost of the energy constraint in (Eq.33). Eq.35 expresses the relationship discussed in section 6.1, indicating that the allocated power and operation time for the equipment in each timeslot will be limited to the unit of time planning T.

Fig. 6 shows the proposed decision algorithm for engaging in a DRP. In the next section, a computational experiment is presented.

7. A computational experiment

The proposed methodology has been implemented in a metal component manufacturing factory. Employing the industrial DR information model in Fig.1, EMS and ERP will provide information on the amount of energy and associated cost required for a production plan. Accordingly, deferrable and non-deferrable loads of equipment have been determined, with ten press machines ($m_D = 10$) being identified as having deferrable loads (L_D) in the press shop factory.

The energy, cost and power of electricity for 24 ($n = 24$) hours of production is shown in Table 2. The energy price before implementing the DRP is 0.25 \$/kW.h. A day-ahead demand response program has been offered with energy prices and energy limits shown in Figs. 6 and 9 for 24 hours; otherwise, without participation in the DRP, the price of electricity is 0.4 \$/kW.h. Accordingly, the time unit of planning, T is calculated by (Eq.18) such that $\mathrm{T} = 1$. Using this primary information, the industrial unit will make a decision as to whether to accept the DRP or reject it. The implementation of the proposed methodology is as follows.

7.1. Selection criteria: implementing the Delphi methodology

As the first step of the proposed methodology (Fig.4.), ten experts from the departments of quality control, quality assurance, sales, engineering and production form the experts' panel. All the experts hold a Bachelor degree. The experts answered the questions about the potential effects of implementing a DRP on the operations management factors presented in Fig. 3. By executing the Delphi procedure presented in Fig.4, consensus was achieved after four rounds of Delphi polling with zero variance in responses and 26 criteria (c = 26) were selected, as shown in Table 3. Criteria 1 to 4, availability of reserved capacity, manufacturing lead time, operation cycle time, and number of bottleneck stages were elicited from factor 2, the production method. This means that these criteria are able to evaluate the effect of participating in a DRP on the production method. Similarly, loss of customers and decreased customer satisfaction are the criteria by which the system is able to evaluate the effect of implementing a DRP on F4, the marketing factor, and so forth. None of the experts believed that the DRP would have an effect on factor one, materials, in this case.

Table 2
Energy demand of equipment (Eqpt) with a deferrable load.

Press machine	c_i (\$)	e_i (kW.h)	Power (kW)	Operation time (h)	AQ_{ij} (Products /KW.h)
Eqpt1	25.00	100	10	10	15
Eqpt2	27.50	110	10	11	12
Eqpt3	50.00	200	10	20	10
Eqpt4	22.00	88	8	11	11
Eqpt5	15.00	60	6	10	13
Eqpt6	18.75	75	5	15	15
Eqpt7	30.00	120	10	12	10
Eqpt8	15.00	60	4	15	12
Eqpt9	25.00	100	10	10	13
Eqpt10	20.00	80	8	10	14
Sum:	248.25	993	81	124	

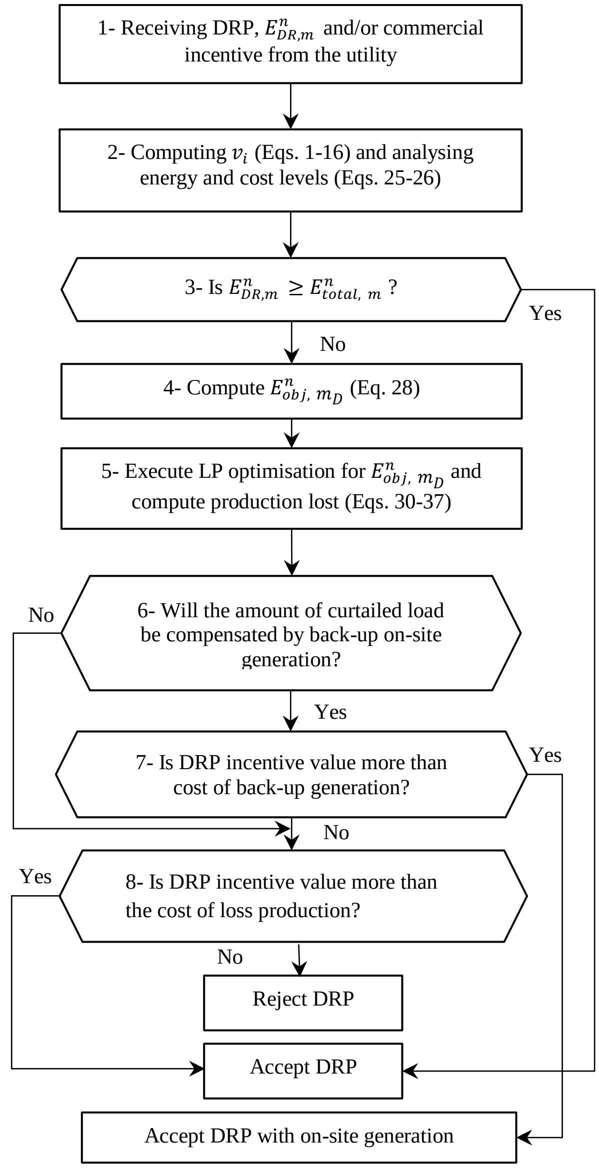

Fig. 6. Decision-making algorithm for assessing DRP engagement

7.2. Decision-making

In this stage, the energy manager will prioritise the equipment based on the selected criteria and specify the importance of each piece of equipment if an organisation participates in a DRP. As there are 26 criteria (c = 26) and ten press machines, the dimension of decision matrix X in equation (1) is 10×26. Using the TOPSIS methodology, the matrix will be simulated for 24 (number of timeslots) times. Following the second step of our proposed methodology and the algorithm presented in Fig. 6, the TOPSIS methodology presented in section 4 is implemented in MATLAB R2016a (64bit) on an Intel Core i7-3770S CPU @3.1 Ghz computer with 16 GB memory with timing performance of three seconds.

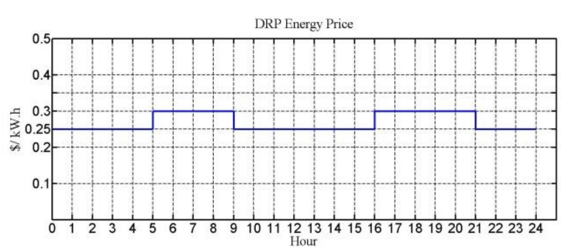

Fig. 7. Day-ahead DRP scheme

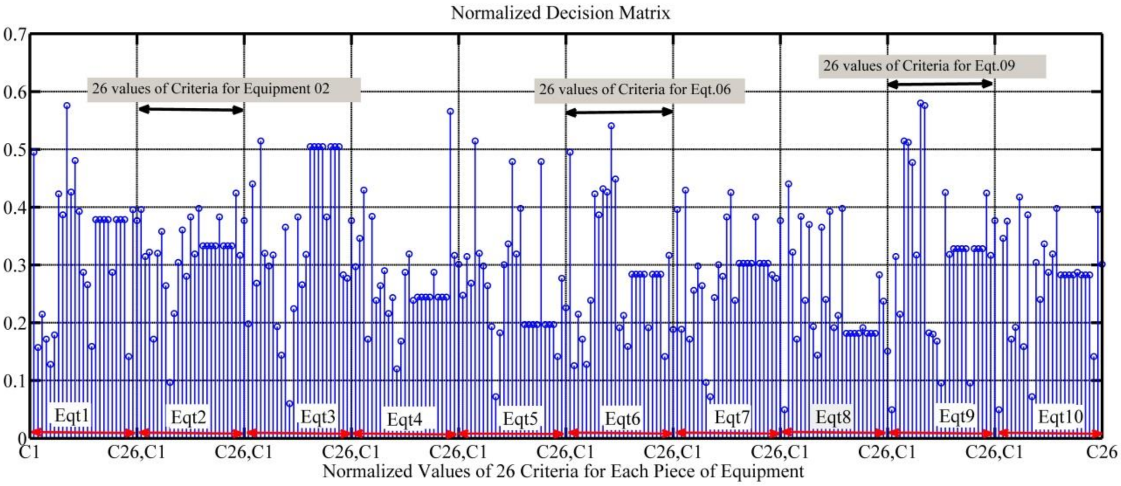

Fig. 8. Normalized decision matrix ($\boldsymbol{N_{10\times 26}}$)

In the following, the intermediate TOPSIS calculations have been omitted for conciseness; however, the normalised matrix (Eq.9) and the TOPSIS final result (Eq.16) are shown in Figs. 8 and 9, respectively. Fig.9 shows that press machines 1, 6, 2, and 9 have high ranking levels while press machines 3 and 10 have the lowest rank. In this experiment, the energy manager weights of (Eq.6) are assumed to be equal for all criteria; however, the effect of this weight aggregation is discussed in section 8.

7.3. Optimisation step

In this section, before performing the optimisation technique, the energy and cost levels such as ($E^n_{total,\ \boldsymbol{m_D}}$, $C^n_{total,\ \boldsymbol{m_D}}$)= (993 kW.h, \$248.25), ($E^n_{total,\ \boldsymbol{m_{ND}}}$, $C^n_{total,\ \boldsymbol{m_{ND}}}$)= (628 kW.h, \$157), ($E^n_{total,m}$, $C^n_{total,m}$) = (1621 kW.h, \$405.25) have been computed by (26, 27). DRP requires the total energy limit of $E^n_{DR,m}$ = 1503 kW.h which is less than the total required energy $E^n_{total,m}$= 1621 kW.h. Following step 4 in Fig. 6, the ($E^n_{obj,\ \boldsymbol{m_D}}$, $C^n_{obj,\ \boldsymbol{m_D}}$) = (875 kW.h, \$ 234.5) is computed by (28) and (29). The amount of total objective energy and the cost level for each timeslot, δ_j and Υ_j, is shown in Figs. 10 and 11. IBM ILOG CPLEX 12.6.1 is employed to simulate the LP optimisation model on the same computer with timing performance of one second. The optimisation results are shown in Figs. 12, 13 and 14.

Fig. 12 shows the amount of energy used in each unit time of planning by each piece of equipment. For example, in timeslot 1, press machines 1, 2, 6, and 10 are operating with energy levels of 10, 10, 5 and 10 kW.h, respectively. However, in the second timeslot, press machines 1 and 9 will stop while press machines 2 and 6 will continue their operations. Meanwhile, press machine 7 will start its operation with an energy level of 10 kW.h. This simulation, illustrated in Fig. 11, shows how the proposed methodology shifts the equipment load. For example, equipment 1 is shifted from t1 to t10-t16 and then to t22- t24, or equipment 2 from the first timeslot, t1, is shifted to t4, t11-t16, and t23-t24. These simulation results indicate that the trend of total optimised energy profile in Fig. 12 is exactly compatible with the energy objective level profile presented in Fig.10 so that $\boldsymbol{E^n_{obj,m_D}} = \boldsymbol{E^n_{opt,m_D}}$ = 875 kW.h. Analyses and a comparison of Figs. 9 and 13 confirm that the equipment with higher priority values received the total energy while the energy for the equipment with low values, such as equipment 3-5, 8 and 10, was curtailed. Furthermore, the amount of production loss associated with this energy curtailment was calculated by (Eq.24) as shown in Table 4. For example, according to the production plan, press machine 3 was supposed to use 127 kW.h of energy to produce 1270 parts, but by participating in a DRP and after optimization, this press will only receive 54 kW.h of energy, which is a reduction of 73 kW.h, equalling 730 parts.

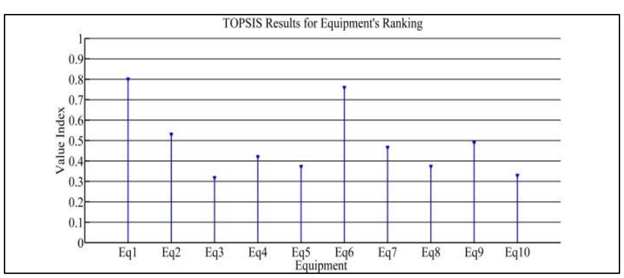

Fig. 9. Equipment ranking

Table 3
List of criteria for assessing the risk of DPR engagement.

C	Factors	Criteria	Sign
C1	F2	Availability of reserve capacity	+
C2	F2	Manufacturing lead time (hour)	-
C3	F2	Operation cycle time (second)	-
C4	F2	Number of bottleneck stages	-
C5	F3	Pressures from top management	-
C6	F4	Loss of customer	-
C7	F4	Customer satisfaction	+
C8	F5	Delivery lead time (hours)	-
C9	F5	Frequency of the deliveries	+
C10	F5	Adherence to schedule	+
C11	F5	Overall machine flexibility	+
C12	F5	Delivery priority	+
C13	F6	Re-calibration and set-up time (minutes)	-
C14	F6	Impact on equipment's safety	-
C15	F7	Effects on hazard analysis and critical control points (HACCP)	-
C16	F8	Scrap and rework cost ($)	-
C17	F8	Operating cost ($)	-
C18	F8	Maintenance cost ($)	-
C19	F8	Tooling cost ($)	-
C20	F8	Establishment and set-up cost ($)	-
C21	F8	Personnel cost ($)	-
C22	F8	Profit per product ($/Product)	+
C23	F8	Penalties due to short quantity or late delivery ($)	-
C24	F9	Number of people involved in stopping the line due to re-set up	-
C25	F9	Operator's dissatisfaction	-
C26	F10	Emissions per product	-

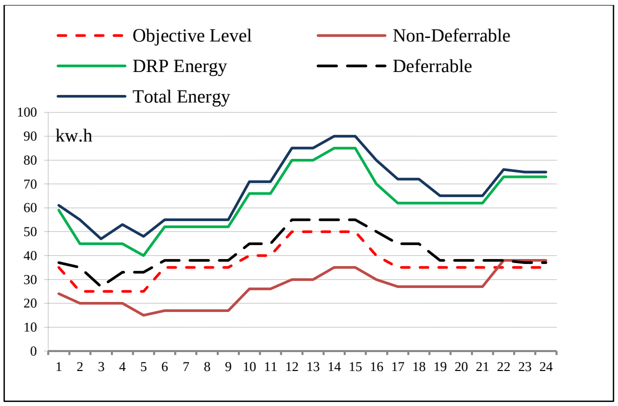

Fig. 10. The energy levels δ_j, $E^{24}_{total,m}$, $E^{24}_{total,ND}$, and $E^{24}_{total,D=10}$

7.4. Discussion

- The number of lost assembly products as a result of participating in this DRP can be calculated from the maximum amount of production loss. In this experiment, Eqpt. 3 has the maximum amount of production loss of 730 parts meaning that 730 assembly products have been lost. Hence, if the unit of profit for each product is considered as one, the company has lost 730 units of profit.

- Before DRP participation, $(E^{n}_{total,\ \boldsymbol{m_D}}, C^{n}_{total,\ \boldsymbol{m_D}})$ were equal to (993 kW.h, \$248.25). After implementing the proposed methodology and curtailing 118 kW.h of energy (Table 4), the value of these parameters reached the objective level (875 kW.h, \$234.5) which means a saving of \$13.75 and a loss of 730 unit of profit.

- Moreover, if the enterprise does not accept the DRP and accepts the flat rate of 0.4 \$/kW.h, then $(E^{n}_{total,\ m}, C^{n}_{total,\ m})$ will which changed from (1621 kW.h, \$405.25) to (1621 kW.h, \$648.4), which means an additional electricity cost of \$243.15.

- The energy manager can use this information to make a final decision by answering the three questions asked in steps 6, 7 and 8 of the proposed algorithm, shown in Fig. 6. If the on-site generator is capable of producing 118 kW.h of energy and assuming that the benefit of each product is equal to \$1, then accepting this DRP will result in the enterprise losing \$716.25 (= \$730 - \$13.75) which is far more than \$243.15. If the cost of on-site generation is added, this difference will increase and the DRP will be strongly rejected.

- Assuming that the benefit of each product is equal to \$0.1, by accepting this DRP, the enterprise will lose \$59.25 (=\$73 - \$13.75). In this case, if the price of onsite generation is less than \$183.9 (=\$243.15-\$59.25) and the generator is able to generate 118 kW.h of energy, then the DRP will be accepted.

- The cost of running generators in every industrial unit depends on the type, size, and fuel, as well as many other generator factors that are not in the scope of this paper.

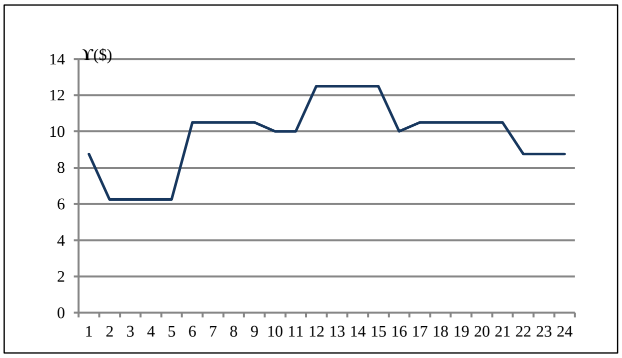

Fig. 11. Associated cost of objective energy level in each timeslot (Υ_j)

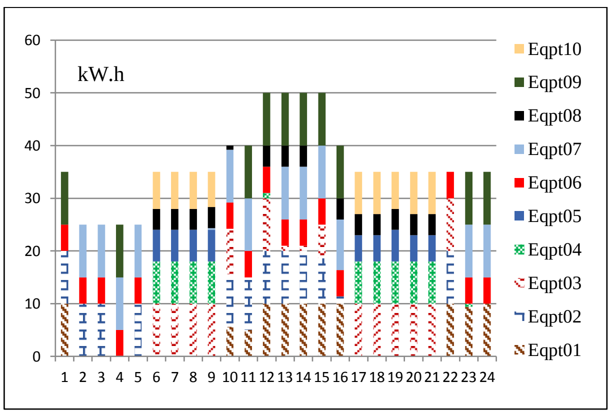

Fig. 12. Production energy assignment based on DRP (E_{ij})

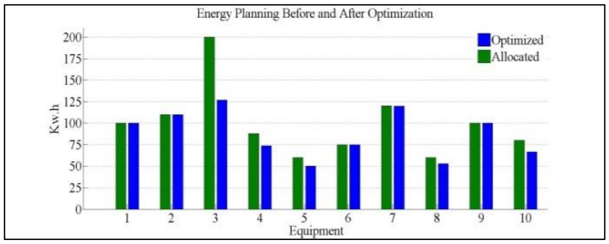

Fig. 13. Energy planning before and after optimization

Table 4
Summary of Energy and Production Loss.

Equipment	Energy level after optimization during 24 hours (kW.h)	Energy loss (kW.h)	Product loss (parts)
Eqpt3	127	73	730
Eqpt4	73.6	14.4	158
Eqpt5	50	10	130
Eqpt8	52.8	7.2	87
Eqpt10	67	13.4	188
sum		118	

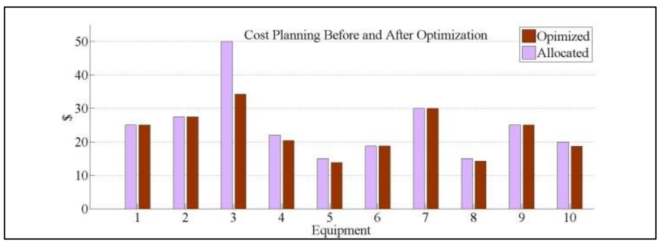

Fig. 14. Cost planning before and after optimization

8. Decision-making sensitivity analysis

As described in the previous section, the simulation of the proposed algorithm was executed when the decision maker (DM) weight vector λ_g, was equal to one for all criteria. In the proposed methodology (Eqs.6 and 7), the energy manager as an expert can increase or decrease the aggregated weight of the criteria w' by vector λ_g. In this section, the sensitivity analysis for studying the effect of decision making on the optimisation model will be examined by comparing the following four scenarios:

Scenario 1: The experiment described in section 7 is the first scenario when the value of vector λ_g is equal to 1 for all criteria and the decision maker is neutral for positive and negative criteria (Eqs. 6 and 7). λ_g and the computed v_1 in Figs. 15 and 16 belong to this scenario.

Scenario 2: In this scenario, the energy manager gives weights to the positive criteria which are ten times stronger than the negative criteria. In other words, it makes the effect of the negative criteria on decision-making ten times weaker than the positive ones. As a result, the alternatives (press machines) which have a larger value in the positive criteria become more preferred.

Scenario 3: In this scenario, the energy manager gives weights to the negative criteria which are ten times stronger than the positive criteria. In other words, the effect of the positive criteria on decision making will be ten times weaker than the negative criteria. As a result, the alternatives which have a lower value in the negative criteria are more effective in the ranking process.

Scenario 4: In this scenario, the decision maker gives weights to criteria 16 to 23 (Table 3) which are ten times stronger than the other criteria. As shown in Table 3, these criteria belong to the financial management factor. As a result, the decision maker decides to increase the value of the criteria which has an effect on cost.

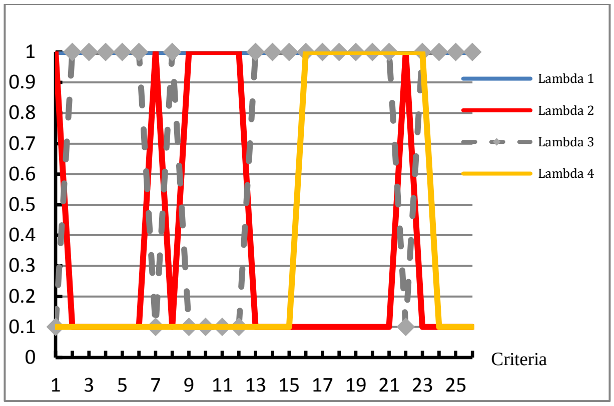

Fig. 15. Weight vector $\lambda_g$in four scenarios

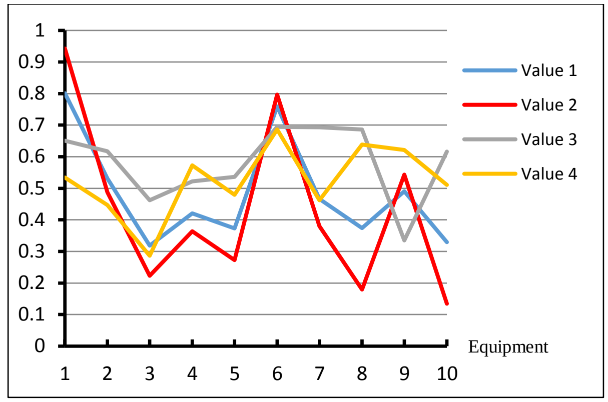

Fig. 16. TOPSIS result computed for four scenarios

Table 5
The optimization result for four scenarios

Eqpt	Allocated Energy After Optimization (kW.h)				Product Lost (parts)			
	S1	***S2***	***S3***	***S4***	***S1***	***S2***	***S3***	***S4***
1	100	100	100	100	0	0	0	0
2	110	110	109.83	92	0	0	2	216
3	127	182	182	127	730	180	180	730
4	73.6	73.6	73.6	88	159	159	159	0
5	50	50	50	51	130	130	130	117
6	75	75	75	75	0	0	0	0
7	120	110.77	120	102	0	93	0	180
8	52.8	52.8	60	60	87	87	0	0
9	100	100	37.5	100	0	0	813	0
10	66.67	20.83	67	80	188	829	181	0
∑ =	875	875	875	875	1293	1476	1464	1243

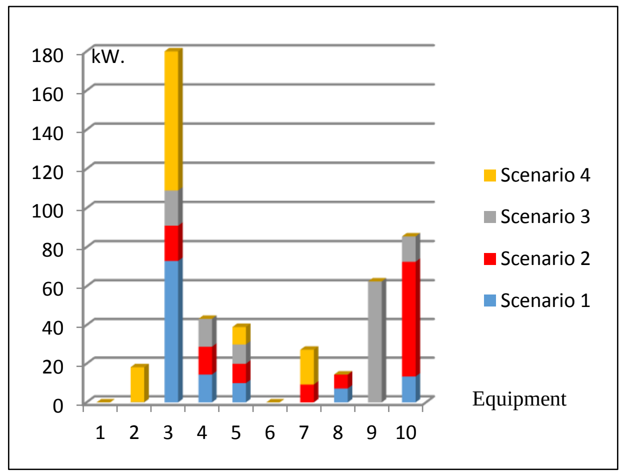

Fig. 17. Energy Lost in Each Scenario

Parameters λ_g and v_i are computed using the TOPSIS method for these four scenarios, as shown in Figs. 15 and 16. Table 5 summarises the optimisation result and Fig. 17 shows the amount of energy lost in each scenario. The results achieved for each scenario are as follows:

- After optimisation, the energy allocated to all the equipment in the four scenarios, as shown in Table 5, is equal to $E^n_{obj,D}$=875 kW.h, which indicates the robustness of the proposed optimisation model.
- As shown in Fig.15, equipment 1 and 6 have the highest value computed by the TOPSIS method in all the scenarios whereas equipment 3 has the lowest value. As a result, as shown in Fig.17, equipment 1 and 6 received the total required energy and equipment 3 received the maximum energy curtailment.

- In scenarios 2 and 3, when weight λ_g for the positive criteria changes from maximum to minimum values, (in comparison to the negative criteria), equipment 8, 9 and 10 have the greatest change in profile "v" , as shown in Fig. 16. The effect of this variance can be interpreted in product loss for this equipment, as shown in Table 5.

9. Conclusions

A new methodology has been proposed and implemented to assess the effects of engaging in a DRP on the operational and production management of a SG. This assessment is essential in making the correct decision on the engagement of a DRP or the employment of distributed energy resources to access the energy required for non-interruptible production.

The literature review in section 3 revealed that existing research is primarily focused on energy management by minimising energy costs while considering production constraints, machine operations and maintenance, and inventory management to make throughputs as efficient as possible by utilising linear and non-linear programming models. But, to the best of the authors' knowledge, no research has yet focused on evaluating the feasibility of DRP in terms of supporting operations managers in the decision-making process in relation to DRP adoption. The existing research could be useful when manufacturers have made the decision to participate in a DRP; however, prior to making this decision, they need to investigate the potential gains and losses associated with doing so. Furthermore, the associated risk of energy loss is not limited to production management; it is an energy efficiency and productivity matter.

As industries differ in relation to products and processes, the Delphi method is utilized to determine the most suitable criteria to assess DRP engagement. As a result, twenty-six criteria were selected in ten organisational domains. The TOPSIS method is employed to assist the energy manager to rank the equipment according to its significance, based on the criteria determined using the Delphi method.

The main contributions and conclusions are:

- According to our literature survey, most of the existing approaches used in the industrial sector of the SG investigate DRPs after they have been accepted and implemented, however there is no approach to investigate the feasibility of engagement in a DRP from the manufacturer's perspective. As a result, our approach is based on the equipment with a deferrable load which is more flexible and agile in production planning. Therefore, we proposed that the amount of energy which is committed to be curtailed by engaging in a DRP should be from equipment with deferrable loads. This level of energy was determined based on the correlation of energy, cost and power.
- A linear programming model was proposed and implemented to utilise the ranking values to optimise energy consumption while satisfying the energy limit posed by production demands. Unlike the other research discussed in the literature review which mostly focuses on minimising cost as their optimisation objective, this paper proposes to maximise energy use to increase production while considering the utility and production constraints.
- An algorithm was proposed and implemented to assist energy managers to decide whether to participate in a DRP. This methodology was implemented in a press-shop factory and the results showed that the equipment with high priority values in relation to the selected 26 criteria received more energy allocation while the DRP essentially only affected the equipment with low priority values.
- Sensitivity analysis was carried out for the four scenarios and a comparison of the results of each scenario indicted the robustness of the optimisation model. The constraints used in the proposed model are the minimum constraints required for energy assignment; however, depending on the nature of the process and products, different production methods may impose more criteria and constraints on the model.

In the introduction, we stated the objectives of this study by posing seven questions. Some of these objectives were restated by explaining the contribution of this paper in this section. To sum up, the Delphi and TOPSIS methodologies can be used to assess the effects of DRP engagement on operational management to minimise the risk associated with participation in a DRP. The literature survey showed how participation in a DRP can impact the functional factors of operational management such as materials, methods, supply chain management and agility, and machines and demonstrated the effects of DRP engagement on operational and managerial factors. Using the Delphi method enabled different departments of an organisation to work together to coordinate the local sensing of the risks posed by DRP participation. The TOPSIS method helped the operation manager to decide to curtail energy to respond to demand (DRP) by considering the equipment's priorities. The proposed optimisation model moved equipment with a deferrable load to a non-peak period by reflecting the operational risk factors in energy planning. Finally, the proposed decision support algorithm assisted the operation manager to decide whether to participate in a DRP or use on-site generation, or to accept the high cost energy for their operation.

Despite the positive results of the proposed decision support algorithm and the past research efforts described in this paper, there may be other areas of opportunity for future research:

1- The main aim of this paper is to present an algorithm to assess demand response engagement. However, to avoid complexity, we do not present a DRP energy price forecasting model in the proposed algorithm.
2- The proposed decision support algorithm can be extended and customised by adding more production variables as criteria in the decision-making stage, such as overall equipment effectiveness (OEE), machine setup time, single minute exchange

of dies (SMED), takt time, and proactive and preventive maintenance. We did not have access to precise information on these factors during the writing of this paper.

3- The proposed model can be extended by considering some uncertainties associated with energy generation and consumption or even forecasting.

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