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Analysis of energy saving potentials in intelligent manufacturing: a case study of bakery plants

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Abstract

To address the global challenge of the climate change, more strict legislations worldwide on carbon emission reductions have put energy intensive industries under immense pressure to improve the energy efficiency. Due to the lack of technical support and financial incentives, a range of technical and economic barriers still exist for small-medium enterprises (SMEs). This paper first introduces a point energy technology, which is developed for SMEs to improve the insight of the energy usage in the manufacturing processes and installed in a local bakery. Statistical analysis of electricity consumption data over a seven-day period is conducted, including the identification of operational modes for individual processing units using an enhanced clustering method and the voltage unbalance conditions associated with these identified modes. Two technical strategies, namely electrical load allotment and voltage unbalance minimisation, are then proposed, which could attain more than 800 kwh energy saving during this period and the current unbalance could be reduced to less than 10%. In addition, the genetic algorithm is deployed to solve the job shop scheduling problem based upon the commercial electrical tariffs, and this reduces the electricity bill by £80 per day in the case study. Implementation of the recommendations based on the above analysis therefore may potentially yield significant financial and environmental benefits.

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1. Introduction

The anthropogenic climate change and global warming have become a global issue in the last decade[1]. To meet the challenges, the UK government has committed to reduce its greenhouse gas/carbon dioxide emissions (GHG) by 80% by 2050 (compared to the 1990's level) [2] . As a part of the commitment to lower GHG emissions, the government has made the reduction of industrial energy consumption a priority [3]. To ensure the same level of production yields, improving the energy efficiency of processes and machinery is a key strategic objective for energy demand reduction [4]. Manufacturing is one of the largest energy consuming sectors, accounting for 16% of annual usage, and should consider the GHG reduction target as a priority [5]. The bakery industry, which produces staple foods such as fresh and frozen bread, cakes and other pastries to meet people's daily dietary demand, consumes a lot of energy from gas and electricity [6]. The UK-based government organization, the Carbon Trust reports that the total energy consumption is 2,000 GWh per year for UK baking industries [7]. Therefore, it is of significant importance to improve the energy efficiency of the baking processes.

Most baked products have a similar manufacturing procedure with flour, water and yeast, and modern baking factories are often equipped with highly automatic production lines [8, 9]. In the production line, since the baking oven consumes a high proportion of energy, many recent researches focus on the computational modelling of ovens for energy reduction [10]. A systematic approach is presented to guide the reduction of energy usage in industrial ovens through five stages: define, measure, analyse, improve and control [11]. Computational fluid dynamics (CFD) analysis of temperature distribution and air flow in 3-zone small scale forced convection bread-baking oven is investigated [12]. [13] introduces an optimization method using a combination of computational approach and experimental heat transfer coefficient estimation throughout the baking process. Analysis of the life cycle cost for different types of ovens such as electric, oil-fired and gas-fired ovens is presented [14]. It is indicated that the flue gas from bake oven could be used to heat water to improve energy utilization. Experimental studies and mathematical modelling for baking are reviewed in [15]. Furthermore, efforts have also been made to investigate mixer, prover and cooling technology for the bakery industry [16]. [17] discusses the modelling of the dough structure formation process within the mixer. The topic of developing a mathematical model to describe the fermentation process in a prover is investigated in [18]. Spiral cooling technology is recommended to reduce the temperature by ambient cooling and refrigeration [19]. Most work mainly concentrate on a single process with fundamental or mathematical models, which imposes technological limitations on a whole-factory approach to energy reduction. Modern manufacturing is generally composed of a complicated production line integrating many sub-processes. Besides each single process, a holistic consideration of the process chain should be taken into account to achieve greater energy saving potentials.

In the holistic approach to achieve industrial energy reduction, the clustering analysis has been shown as a very useful tool to understand the operating conditions for a sub-process in the production line[20]. Numerous clustering methods have been investigated in industrial applications. K-means is a classical clustering method which divides a dataset into a pre-defined number of partitions. Although k-means can be implemented easily, it is sensitive to outliers and noise, and it is difficult to find suitable initial centroids [21]. Fuzzy c-means clustering is effective, but random selection of centres may cause the iterative process fall into a local optimal solution [22]. Density-based spatial clustering of applications with noise (DBSCAN) is primarily an algorithm used in data mining, which could detect clusters of arbitrary scales and shapes as well as distinguish the noise points [23, 24]. The algorithm has two parameters to be pre-defined, namely, the radius Eps and the minimum points within radius $MinPts$, which have to be carefully tuned. Therefore, [25] provided an enhanced DBSCAN algorithm, which could determine two density related parameters based on a k-dist curve for varied-density clustering.

Based on quantifying the energy consumption and classifying the operational mode of machines in a local bakery company, this study aims to develop techniques and algorithms that can be employed to optimise the energy utilisation in the manufacturing process. This paper first introduces the point energy technology developed by the research team for small-medium enterprises (SMEs) to improve the insight of the energy usage in the manufacturing processes (www.pointenergy.org), which has been used at different industrial sectors, including the local bakery company in this case study. The system collects energy (e.g. electricity, gas and oil) usage data at the component level of a baking process. For electricity usage, real-time data recorded include voltage, current, power factor and frequency, etc. Then statistical analysis on the collected data is conducted, including operating conditions and voltage unbalance rates of machines at different operational modes. With the value of $MinPts$, the optimal Eps value of an enhanced DBSCAN can be determined by the k-dist curve plot automatically. Based on the statistical analysis results, methodologies are then developed to optimise operational schedule of the production line with the objectives of energy efficiency and economic performance. The remainder of this paper is organised as follows. The preliminaries relating to bakery process, the point energy platform and the enhanced DBSCAN algorithm are introduced in section 2. In section 3, the statistical analysis on energy consumption of different machinery tools is presented in detail. Section 4 details the methodologies for energy efficiency improvement and flexibility study. The job shop scheduling optimisation from the economic aspect is given in section 5. Finally, section 6 concludes this paper.

2. Preliminary/related work

Internet of things (IOT) techniques have been intensively researched and developed to improve the energy efficiency in industry recent years. While a range of technical and economic barriers still exist for SMEs due to lack of technical support and financial incentives. The research team of authors have developed point energy platform for SMEs. This section gives a brief introduction to the basic production process in this case study, the point energy platform developed by team and an enhanced DBSCAN algorithm.

2.1. Bread production process

Figure 1 is an illustration of a general bread production process, which mainly consists of ingredient mixing, dough proving, bread baking and cooling. During ingredients mixing, the raw material (flour, water and other ingredients) are added to a large mixer and thoroughly intermixed; then the dough out of mixer is sliced and formed into product sized portions which are sent to be proved by a hoist conveyor. The proving stage (also referred to as proofing) subjects the dough pieces to an elevated temperature and high humidity environment. The proofed dough pieces are then sent to the oven, starting the baking process, which encompasses a series of simultaneous heating, and water vaporing process, which eventually produce the bread. Once the loaves are baked well, they are removed from their moulds automatically by a pneumatic depanner. Then the baked loaves are cooled and waiting for packaging. Since temperature reduction is a time consuming process, the cooling conveyor moves at a slow speed. Finally, the bread is ready to be sliced and packaged, concluding the manufacturing process.

2.2. Point energy platform

A desire for more detailed knowledge of power consumption, both in terms of increased sampling rate and different granularity of use location has driven the development of the point energy platform (www.pointenergy.org). Measurements of whole-factory power consumption as well as individual machinery equipment is achieved using a combination of current transformers, interfaces to existing meters and customised smart meters. The system has been field-tested in different industrial sectors including a local bakery company which is eager to

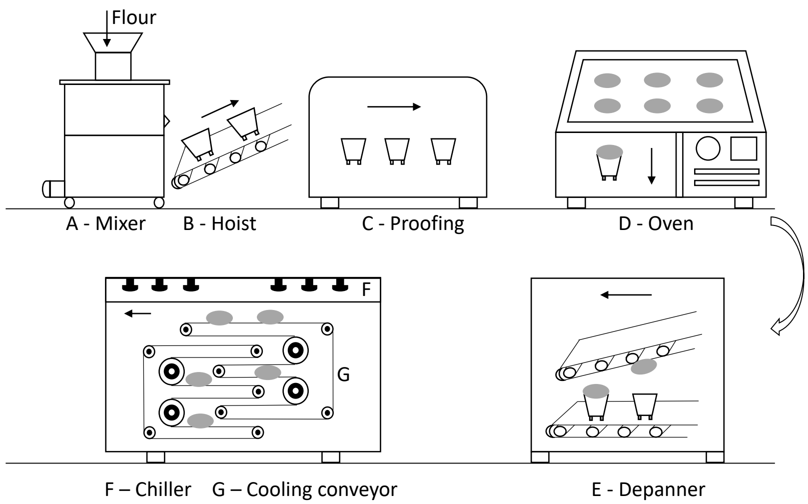

Figure 1: The manufacturing production line of bread: A.Mixer; B. Hoist; C. Prover; D. Oven; E. Depanner; F. Chiller; G. Cooling conveyor

know how much energy they use daily and more specifically, how much energy is consumed by each production line or even each machine. The two parts of the system can be considered as the Data Acquisition layer and the Data Analytics layer, bridged by an on-site base station, detailed in figure 2.

Data acquisition of electrical power usage is performed by microcontroller nodes (Multitech MDOT) that are interfaced to ABB B24 112-100 3ph power meters via Modbus. These meters are installed inside the factory's electrical panels, using hardwired connections for voltage measurements with a current transformer installed on each phase to measure current. As the large machines have independently wired supplies inside the panels, the system is able to gather a granular picture of electricty usage [26]. In addition to this, pre-existing gas and water meters produce pulse outputs which are captured via GPIO triggered interrupts.

The gathered information is sent via the LoRaWAN radio system using the Multitech MDOT's integrated radio, and captured by a Multitech Conduit LoRa concentrator. These LoRa packets are decoded and passed to an on-site server (standard fanless x86 hardware), which performs data concatenation and packaging before sending the readings via MQTT to off-site cloud services. The WAN connection is provided by a 3G/4G mobile signal however the router hardware is capable of taking advantage of ethernet or WiFi connections as well.

The on-site server is also responsible for node management and is capable of local data presentation, with the expectation that actuator control decisions will be implemented at a later stage of development. A dashboard is hosted on a private cloud server which presents the bakery manager with real-time (gauges and dials) and historic (searchable graphs) energy usage information - specifically, electrical power categorised by machine and production line, and gas usage rate for steam and water boilers. The gas usage rate is estimated using a windowed derivative over a 30 minute period which provides a meaningful description of their operational status - it was observed that direct display of the captured pulses is not helpful due to the fixed rate, variable duty cycle operation of the burners. The complete data set is stored in a secured MySQL database which can be accessed by the research team through a command-line interface.

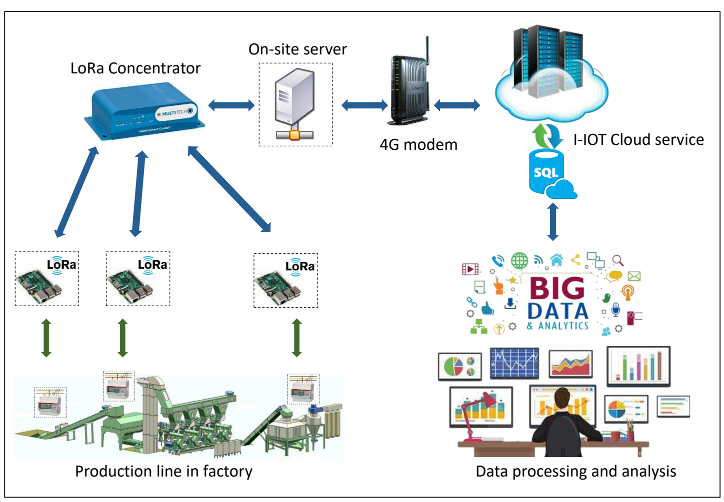

Figure 2: Point energy platform

2.3. The enhanced DBSCAN algorithm

The density-based spatial clustering of applications with noise (often referred to as DBSCAN) algorithm could identify clusters in a large spatial dataset based on the local density of objects. DBSCAN is based on the following definitions with respect to a minimum number of points ($MinPts$) within a minimum distance (Eps).

Definition 1: the Eps-neighbor of point p:

$$N_{Eps}(p) = \{q \in D | dist(p, q) < Eps\} \tag{1}$$

For each point p belonging to a cluster C, there is a point q in C and point p is inside of the Eps-neighbor of point q, which means $N_{Eps}(q)$ should contain at least $MinPts$ points. As shown in Figure 3, the point inside of cluster is defined as core point and the point on the border of cluster is defined as border point.

Definition 2: directly-density-reachable: The point p is directly-density-reachable from point q, if

$$\begin{cases} p \in N_{Eps}(q) \\ N_{Eps}(q)| \geq MinPts \end{cases} \tag{2}$$

Definition 3: density-reachable: The point p is density-reachable from point q if there is a chain of points $p_1, p_2, \cdots p_n, p_1 = q, p_n = p$, and p_{i+1} is directly-density-reachable from p_{i+1}.

Definition 4: density-connectivity: The point p is density-connected to q if there is a point o, such that p and q are density-reachable from point o.

The classical DBSCAN algorithm requires two parameters, Eps and $MinPts$, the accurate estimation of which is a critically important task for good performance. For the enhanced DBSCAN, the optimal Eps could be determined by the first sharp change on k-dist curve automatically [25]. The pseudo code is illustrated below.

Algorithm: The enhanced DBSCAN algorithm

FUNCTION DBSCAN main (Dataset D, $MinPts$)

begin
call k-dist curve to calculate Eps automatically $wrt.$ D and $MinPts$
for (all points in D) **do**
retrieve the Eps-neighbor of point p:
if ($|N_{Eps}(p)| < MinPts$) **do**
mark the point as noise point and return
else
selcect a new cluster id
mark all points in $N_{Eps}(p)$ with this cluster id
put all points in $N_{Eps}(p)$ in the seed queue
while seed queue $\neq \phi$
random point =seed. top ()
retrieve the points in seed queue:
if ($|N_{Eps}(seed.top)| \geq MinPts$)
if (all points in $N_{Eps}(seed.top)$ marked noise or not marked) **do**
mark all points in $N_{Eps}(seed.top)$ with current id
put them into seed queue.
end if
end if
end if
end for
end

FUNCTION k-dist curve (Dataset D, $MinPts$,)

for (all points p in D) **do**
compute the Euclidean distance of p to its $MinPts$-th nearest neighbour
plot the distance values in ascending order
detect the sharp change that corresponds to the optimal Eps
return selected Eps value
end for

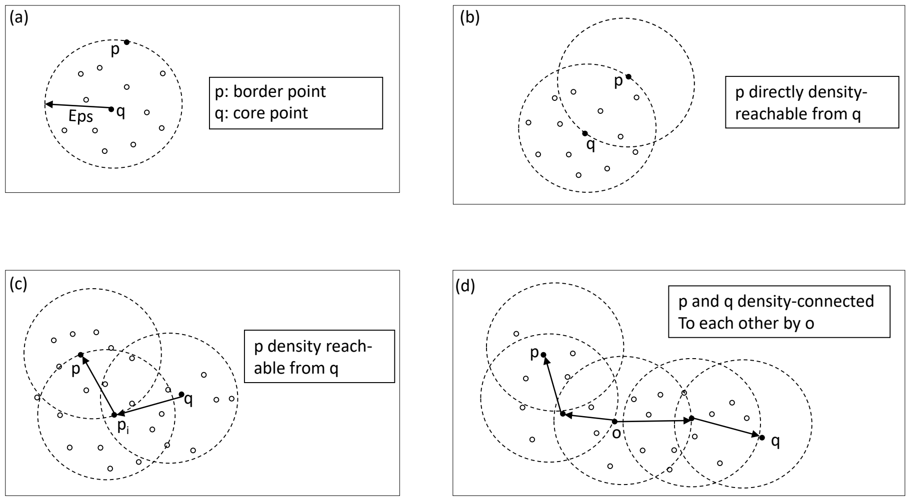

Figure 3: The illustration of DBSCAN algorithm

3. Statistical analysis on energy data

3.1. Collected energy data

This paper documents the energy data of a single production line working with three-phase 415V AC power over a randomly selected seven-day period, the week beginning from Monday 2nd Jan. 2017. The following features were monitored at a five minute interval across all three phases: frequency, voltage, current, active power and power factor.

Table 1 summarizes the daily electric energy usage of the instrumented bakery production line for each process unite over the entire week. It is obvious that each unite has a different energy consumption pattern every day. The weekly peak demands occur on Thursday (1212.43 kwh) and Friday (1222.73kwh), while the troughs are on Saturday (1020.14 kwh) and Sunday (1130.6 kwh). This is caused by the factory running lighter shifts on the weekends due to labour costs and decreased customer demand. According to the total energy consumption, the oven, the depanner and the smaller chiller are the three pieces of equipment with the highest electrical energy usage in the production line, consuming 2643.86 kwh (32.62% of the total), 1697.95 kwh (20.95%) and 1774.68

kwh (21.90%) respectively. Apart from the large chiller that is turned off most time, the hoist used the second least amount of energy, only 330.76 kwh, equivalent to 1.9% of the total energy usage. The next lowest energy-consuming unites are the prover and the cooling conveyor, at 440.89 kwh (5.44%) and 450 kwh (5.55%) respectively.

Table 1: energy usage of manufacturing process

Day	Date	Mixer (kwh)	Hoist (kwh)	Prover (kwh)	Oven (kwh)	Depanner (kwh)	Cooling conveyor (kwh)	Small chiller (kwh)	Large chiller (kwh)	Total energy (kwh)
Mon.	02/01/2017	110.6	52.21	64.88	375.29	242.61	62.22	292.17	3.97	1203.95
Tue.	03/01/2017	71.1	44.4	67.08	375.53	265.97	69.63	235.53	39.19	1168.43
Wed.	04/01/2017	80.7	48.13	61.31	372.62	260.03	67.03	217.04	48.97	1155.83
Thu.	05/01/2017	115.5	53.65	65.72	375	246.08	62.47	290.11	3.9	1212.43
Fri.	06/01/2017	111.5	57.12	72.08	373.08	243.07	60.75	301.25	3.88	1222.73
Sat.	07/01/2017	52.5	27.32	45.38	395.31	222.39	63.89	166.62	46.73	1020.14
Sun.	08/01/2017	83.5	47.94	64.44	377.03	217.8	64.01	271.96	3.92	1130.6
Total energy (kwh)		615.52	330.76	440.89	2643.86	1697.95	450	1774.68	150.56	-

3.2. Clustering for operating conditions

For every manufacturing sub-process, the machine status can be identified by the enhanced DBSCAN algorithm. In the experiment, the $MinPts$ was set to be four based on prior research [27], and Eps value was determined by the k-dist curve automatically. For each sub-process, five conditions for each machine can be defined – heavy load, mid-range load, light/no load, standby and power-off.

The full details of each machines loading regime and energy consumption under different conditions are given in Figure 4 and Figure 5. In fact, the proportion of energy consumed by each machine during a given load-state generally reflects the time spent in that state, with the notable exceptions of the mixer and large chiller. The mixer is powered off for the majority of time (about 86% during one week), and works under the mid-range load for 12.21% of time, which accounts for 91.3% of its energy usage. The large chiller is only active for about 9.8% of time, most of which is spent under light/no load, and is responsible for 67.66% of its consumed energy. This could be explained by the fact that these machines consume very little power in the powered-off state in most of the time [28]. In contrast, the small chiller spends more than half of the time (50.65%) under heavy load conditions, which consumes 73.63% of energy and only negligible time (2.6% in total) is spent in power-off condition.

The prover and the depanner are also under heavy load for a significant amount of time, 38.26% and 35.23% respectively. The prover spends the majority of its time under mid-range load (50.16%), however larger energy is used during some shorter over-load periods. As expected, the machines still consume a non-negligible amount of power in the standby state (the hoist is 26.89% of time, consuming 1.89% of its energy). Different from the other machines, the oven was constantly working, with no time spent at the power-off or standby states. Like most of the other machines, the cooling conveyor spends the majority of its time (62.31%) under mid-range load and spends no time in the power-off state.

Overall, the machines spend the majority of their time under mid-range load, with the exception of the small chiller which is under heavy load for significant periods. There is no time spent on the powered off state for the oven and cooling conveyor, which leads to these two machines running more time in the light/no load status than the other machines. The hoist, large chiller and small chiller are all placed in the standby state for more than 25% of the observed period, wasting about 108.27 *kwh* in total. Therefore, some of the machines have sub-optimal operating regimes as indicated by the clustering analysis of their electrical load, which suggests the possibility of schedule based energy saving strategies.

3.3. Voltage unbalance evaluation

According to the IEEE definition of voltage balance [29], the voltage unbalance rate (VUR) can be formulated as follows:

$$\mathrm{VUR} = \frac{\text{max voltage deviation from avg phase voltage}}{\text{the avg phase voltage}} \times 100\% \tag{3}$$

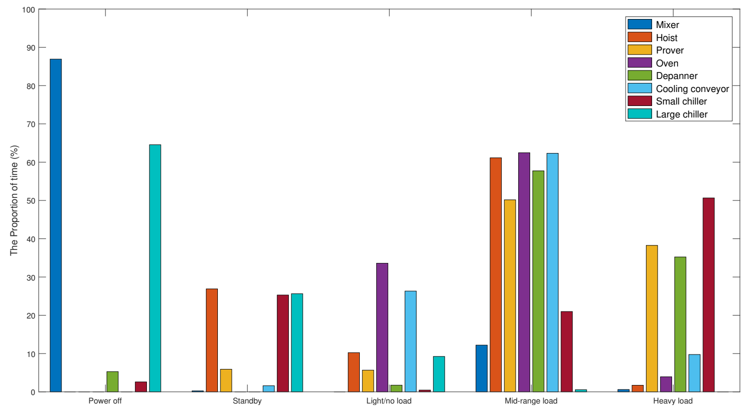

Figure 4: The proportion of time under different working conditions

The voltage unbalance numerical evaluations of each sub-process under different working conditions are shown in table 2. The VUR values of most of the machines are larger than 1%, a maximum value recommended in the literature, which would reduce the efficiency and decrease life of machines [30]. For the large chiller, the VURs of all working conditions are smaller than 1%, which means that the machine is considered to be working in an acceptable environment. Even at the powered off state, the VURs of the small chiller and depanner are still larger than 1%, which implies that there may exist a voltage unbalance in the power supply system itself.

For the cooling conveyor, prover, small chiller and oven, the VUR values of all working conditions are larger than 1%, of which the worst offender is the cooling conveyor under mid-range load, giving a VUR of 1.70%. Conversely, the cooling conveyor on standby also demonstrates one of the lowest VURs (1.14%) of the group. The best and worst-case VURs appearing in different load conditions for each machine have demonstrated some divergence from the expectation of a worsening VUR with increasing load, which underscores the importance of evidence based analysis to characterise machine performance and identify efficiency savings - as well as highlighting the complexity and interconnectedness of a modern production line.

In conslusion, statistical analysis has revealed that there is an underlying

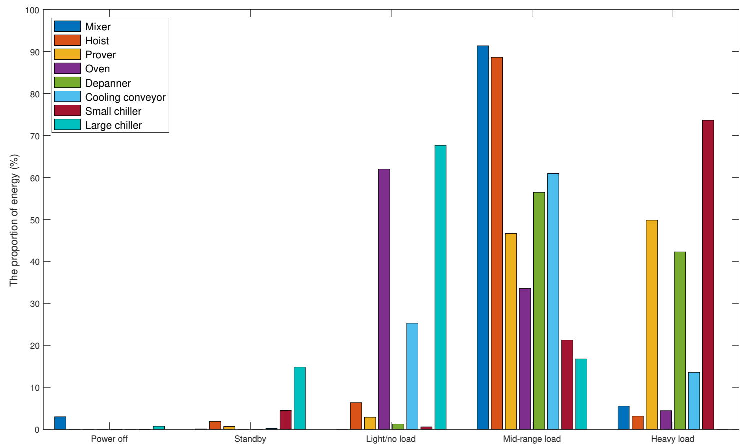

Figure 5: The proportion of energy under different working conditions

Table 2: VUR values under different operating conditions

Operating Condition	Mixer (%)	Hoist (%)	Prover (%)	Oven (%)	Depanner (%)	Cooling conveyor (%)	Samll chiller (%)	Large chiller (%)
Standby	1.04	0.91	1.10	-	-	1.14	1.45	0.54
Light/no load	1.02	1.08	1.35	1.59	1.62	1.39	1.55	0.64
Mid-range load	0.92	0.94	1.40	1.55	1.63	1.70	1.51	0.63
Heavy load	0.99	1.25	1.37	1.31	1.65	1.46	1.62	-
Power off	0.95	-	-	-	1.26	-	1.18	0.58

voltage imbalance in the electrical supply system, and that the electrical loading of some of the machines can have a moderate effect on the local VUR values.

4. Energy efficiency optimization and results

This section is to identify where the energy savings can be made and efficiency can be improved based upon the data analysis performed in the previous sections. Two different strategies for optimising the production system are investigated, with the objectives of reducing unnecessary energy consumption and prolonging the lifetime of the machines, through the consideration of workload allocation and voltage unbalance minimisation. The feasibility and results of these two schemes is also discussed for the case of local bakery plant.

4.1. Workload allocation

Choosing start and stop time reasonably for machines that would otherwise be kept in light/no load or standby states to wait jobs could practically reduce the energy consumption [31]. This does raise the concern whether an increase in machine start-ups will negatively affect lifetime. Table 3 shows the recommended operating cycles for various classes of motors, and indicates how frequently machine can be started along with the minimum rest duration between starts [32]. Working within these stipulations and bearing in mind start-up costs and time, it is recommended that electrical machine should be turned off whenever possible to reduce standby and light/no load time.

The electrical machines are designed at 50% to 100% of the rated load, and technically they have at least the same if not greater efficiency near 75%. The efficiency of machine tends to decrease dramatically when below 50% load [33]. Taking the oven for example, the specific energy consumption would increase by 5% if the load is at 75%, and increase by 16% at 50% load [34]. On the other hand, although most machines are designed with a service factor (a multiplier which indicates how much the machine can be overloaded), running the machine continuously above its rated load will lead to reduction in efficiency and a reduced lifetime. Thus, it is desirable that machines is loaded as near to 75% rated capacity as possible. There are several ways to achieve this, including: i) replacing larger, partially-loaded machines with smaller, fully-loaded ones; ii) optimising the system or process so that the machines could run at 75% of rated load for longer time instead of continually with light/no load or heavy load.

4.2. Voltage unbalance minimisation

The machines have some level of unbalance on three phases, which results in degraded performance and decreased lifetime. For example, the voltage unbalance rate of the cooling conveyor under mid-range load can reach up to 1.7%. The depanner is always working with VUR values which are significantly higher than the recommended maximum. This voltage unbalance leads to unbalanced

Table 3: The start and rest information for electrical motor

Item	2-pole		4-pole		6-pole	
	A	B	A	B	A	B
75	2.9	180	5.8	90	6.6	79
100	2.6	110	5.2	110	5.9	97
125	2.4	275	4.8	140	5.4	120
150	2.2	320	4.5	160	5.1	140
200	1.8	1000	3.7	500	4.2	440

A: the maximum number of starts per hour;

B: the minimum off time (seconds) between starts.

currents, resulting in additional heating [35]. The percentage rise in temperature for a given VUR percentage is calculated by doubling the square of the VUR, i.e. $x\%\text{VUR} = 2(x^2)\%$. For example, the hoist conveyor motor which should work at a room temperature 25°C, would experience an increase of 2°C under the condition of a 2% voltage unbalance, along with the associated increases in losses and wear.

The voltage unbalance also has a detrimental effect on the efficiency of machines. Table 4 indicates the relationship between the efficiency and voltage unbalance for an 1800 revolutions per minute (RPM), 100 horsepower (hp) motor [36]. It can be seen that when working under full load, the machine would be 1.4% less efficient when experiencing a 2.5% voltage unbalance. For a 100 hp motor which runs at full load for 8000 hours per year, the correction of three-phase voltage unbalance from 2.5% to 1% would lead to about 9500 kwh in electricity savings.

Voltage unbalance may be present on the electrical grid supply and/or caused by a large single-phase load. Besides mathematical sensitivity analysis [37], many technologies for eliminating unbalanced voltage exist, including re-distributing single-phase loads, having local utilities to correct unbalanced grid power, or installing passive and/or active filters to reduce the unbalance

Table 4: Efficiency VS VUR in the laboratory

Load (% of rated load)	VUR Nominal	VUR 1%	VUR 2.5%
100	94.4	94.4	93
75	95.2	95.1	93.9
50	96.1	95.5	94.1

(also helpful to dampen harmonics).

4.3. Feasibility and results discussion

In the bakery plant, it is desirable to schedule production in such a way that a machine is operated within its rating envelope and ideally at its peak efficiency. Although for the oven, it needs a long heat-up time, about 30 minutes, which takes the oven from cold to ready, meaning that it is more practical to keep it active at all the time except for the cleaning requirement. Take the cooling conveyor, hoist and depanner as examples, the time from start to ready is only less than 5 seconds, which means it is easily to reduce the energy consumption by reducing the standby and no/light load time. In the selected seven-day period, if these three machines could be turned off automatically after use, which reduces the standby and no/light load time, about 155 Kwh energy could be saved based on the analysis of Table 2 and Figure 5.

In addition, the large chiller is usually powered off, which requires the small chiller to work under a heavy load condition for long periods. It is obvious that the small chiller are under overload conditions for more than 58.8 hours, while the large chiller is powered off, standby or no/light load for about 150 hours. This is in alignment with the actual manufacturing schedule of the factory, which dictates that the large chiller will only be activated when the small chiller cannot satisfy the production demand. In some respects, this can be considered as a misuse of resources. In this example, if the load exceeds the rated capacity of small chiller, it is shut off and the large chiller is started. The capacity of large chiller is twice of that of small chiller in this case, and then the energy

Table 5: Results of energy reduction

Items	Mixer (kwh)	Hoist (kwh)	Prover (kwh)	Oven (kwh)	Depanner (kwh)	Cooling conveyor (kwh)	Small chiller (kwh)	Large chiller (kwh)	Total (kwh)
Reduce standby and no/light load	0	26.46	17.64	0	16.98	112.50	88.73	124.96	387.27
Change heavy to mid-range load	1.19	74.85	46.58	6.15	0.76	15.70	324.03	0.00	469.26

consumption could be saved about 100 Kwh according to the analysis of Table 2 and Figure 4. Hence, there presents an opportunity for better coordination of resources to enhance the overall efficiency of the system. Table 5 illustrates the overall energy saving for machines in the production line based on the previous discussion.

There exist huge voltage unbalance for oven, depanner and small chiller. The smart regulator of three-phase unbalance could be installed, which could compensate the reactive power as well as adjust the unbalanced active current in the bakery plant. In practical applications, the current unbalance could be decrease to less than 10%.

5. Economic benefit analysis

In this section, assuming all machines working at peak efficiency according to the previous section, the scheduling of production process would be discussed based on the commercial tariff in Northern Irealand.

5.1. Electricity consumption and tariff

The hourly electricity usage resulting from the current production schedule over the presented one week period is given in Figure 6. The mean hourly electricity usage shown by the red dashed line is 48.24 kwh. About 81.6% of values fall within one standard deviation of the mean consumption value, which indicates that production configuration generally has a low degree of impact on energy consumption. Several notable peaks do occur at 15:00 on Monday, 16:00 on Wednesday, 19:00 on Friday, and the period of 01:00-04:00 on Saturday. The energy required at these times is about 10 kwh more than the mean value. The notable low energy consumption points are during the periods of 14:00-19:00 on Saturday and 03:00-06:00 on Sunday. The energy used in this period is at least 15 kwh less than the mean energy consumption value.

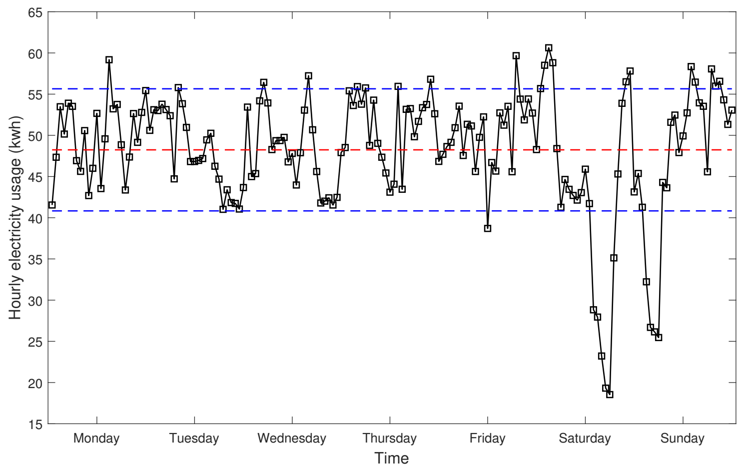

Figure 6: Hourly trend for electricity usage

The bakery company is located in Northern Ireland, and the Northern Ireland Electricity (NIE) Ltd. tariff for commercial factories can be freely obtained [38] and is shown in Table 6. It can be seen that the charge varies a lot between peak-time and off-peak time, on weekdays and weekends and across different seasons. Take the month of January for instance – on weekdays the charge for 22:30-08:00 is just 0.451 p/unit, while the charge between 16:00-19:00 is 23.227 p/unit, over 50 times difference; at the weekend, the daytime rate is 0.905 p/unit the night rate is 0.451 p/unit.

As shown in figure 6, the high energy consumption points are mainly during weekday peak times when the tariff is very high, while the low energy consumption points occurs during the weekend when the charge is very low. This is not unexpected as the tariff is based upon high and low demand periods, however with detailed knowledge of energy requirements in the factory it is possible to make an estimate of the economic effects of shifting peak power periods to the low tariff times.

Table 6: electrical charge for commercial plant

<table>
<tr><th>Week</th><th>Time</th><th>Mar.-Oct.
p/unit</th><th>Nov. and Feb.
p/unit</th><th>Dec. and Jan.
p/unit</th></tr>
<tr><td rowspan="4">Weekday</td><td>0800-1600;
1900-2030</td><td>0.993</td><td>5.615</td><td>12.444</td></tr>
<tr><td>1600-1900</td><td>0.993</td><td>12.089</td><td>23.227</td></tr>
<tr><td>2030-2230</td><td colspan="3">0.905</td></tr>
<tr><td>2230-0800</td><td colspan="3">0.451</td></tr>
<tr><td rowspan="2">Weekend</td><td>0800-2230</td><td colspan="3">0.905</td></tr>
<tr><td>2230-0800</td><td colspan="3">0.451</td></tr>
</table>

5.2. Job shop scheduling problem

The production schedule defines how and when machine and materials will be utilised to make each product. Quotas and order deadlines are dictated by customer demand, however varying degrees of flexibility always exist in how these demands are met. Research on multiple jobs processed by several machines while each job must be performed in a given order is one of the most important industrial activitiesjob shop scheduling (JSS).

In bakery, each kind of bread is produced following a particular number of operations. Each operation has to be performed by a dedicated machine and requires a predefined processing time. The operation sequence for bread is prescribed in a production recipe. Therefore, each kind of bread has its own machine order in production process. Assume that n kinds bread $B = \{B_1, B_2, \cdots, Bn\}$ have to be processed on m different machines $M = \{M_1, M_2, \cdots, M_m\}$. Bread B_k consists of a sequence of m operations $O = \{O_1, O_2, \cdots, O_m\}$ on m machines, which have to be scheduled in order $O_1, O_2, \cdots, O_m$. Moreover, each operation O_i has a processing time T_{ki} for bread B_k. The objective is to find an operating schedule for n kinds of bread such as to minimize a certain function of the electricity cost and completion time.

Genetic algorithm (GA) is an evolutionary process inspired optimization approach, and has been widely adopted in job shop scheduling. Here we use GA to solve the JSS in bakery. The length of chromosome is equal to $n \cdot m$, where n represents the number of bread types and m is the number of machines. Each element in chromosome is a random number between $[1, n]$. The times j ($j \in [1, m]$) that number i ($i \in [1, n]$) appears in the sequence indicates the j-th operation of i-th kind of bread. For example, for a chromosome $\{1\ 2\ 2\ 1\ 2\ 1\}$, the first element stands for the 1-st operation of the 1-st kind of bread; the forth element means the 2-nd operation of the 1-st kind of bread.

In the experiment, the maximum number of generation and population size are both set to be 200. From one generation to the next generation, crossover rate is selected as 0.8 and mutation rate is 0.08. The objective function in GA is a combination of electricity cost and makespan using same weights. A specific example will be described in the following. For simplicity, assuming:

a) There are five kinds of bread to be produced.

b) All machines are working at the 75% rated load.

c) All machines will be turned off immediately after use.

d) The active electrical cost tariff is based on figures for January.

The process time $t = \{t_{k1}, t_{k2}, \cdots, t_{km}\}$ for the k-th kind of bread and the rated load $p = \{p_1, p_2, \cdots, p_m\}$ for each machine are shown in Table 7. The electricity cost could be calculated as:

$$cost = \sum_{j=1}^{J} (\sum_{k=1}^{n} \sum_{i=1}^{m} p_i \cdot t_{ki}) \cdot f_j \tag{4}$$

where p_i is the rated power for i-th machine; t_{ki} is the processing time on i-th machine for k-th bread; J represents the number of electricity rates. f_j means j-th tariff.

Figure 7, Gantt chart, presents the result of optimal scheduling, where different color represents different type of breads. It is observed that the electricity cost of the optimal schedule provided by GA is £127.75, while the highest cost of a random schedule is £209.97, which presents a significant profit for bakery. This energy cost saving can be achieved simply by rescheduling production with

Table 7: information of each machine

Process time (hr)	Mixer	Hoist	Prover	Oven	Depanner	Cooling
Bread type 1	1.6	1.8	3	1.5	2	3
Bread type 2	1.5	2	3.5	1.6	1.5	3.5
Bread type 3	1.7	1.9	2	1.7	1.8	2.5
Bread type 4	1.8	2	2	2.2	2	3
Bread type 5	2	1.8	2.5	1.5	2.2	3.5
Working load (kw)	25	2.5	2.0	15	10	15.5

no capital outlay and no changes required in process, plant or working hours.

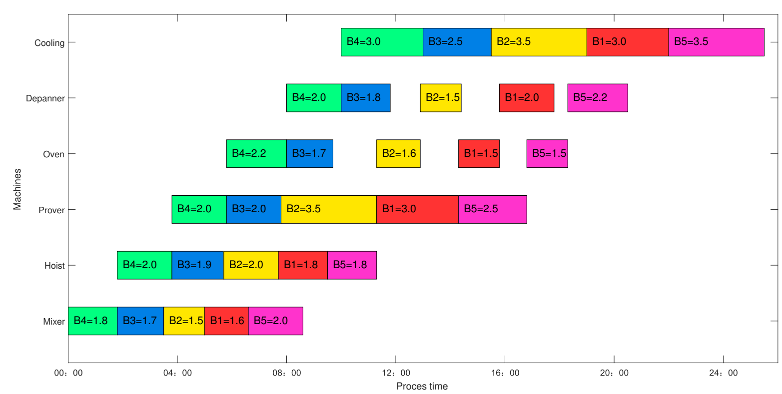

Figure 7: The Gantt chart of optimal scheduling obtained by GA

This example has demonstrated the economic advantages of interleaved production scheduling for different products based upon their power requirements and sub-process timings to maximise resource utilisation and reduce energy consumption.

6. Conclusion

In this paper, the energy monitoring platform developed by point energy technology (www.pointenergy.org) is first introduced, which monitors and records the energy consumption of manufacturing processes at different granularity level.

The data gathered by an installation at one of the core production lines in a local bakery is analysed. The statistical analysis of the energy consumption at each machinery unite over a randomly selected seven-day period in January is conducted. An improved density-based spatial clustering of application with noise approach, which automatically selects the optimal Eps value through k-dist curve plot for a given $MinPts$, is applied for clustering of operating conditions.

The analytic results on the the power energy consumption at one of the production lines in the bakery are summarised as follows: a) The oven, the depanner and the small chiller are the top three energy-consuming process units; b) The hoist and oven are constantly running during the observed period; c) The small chiller is working under heavy load for a significant period of time, while the large chiller is often powered off; d) The oven and cooling conveyor have no power off states during the observed period, which leads them running much time at no/light load status; e) Most of the machines exhibit a significant level of voltage unbalance.

Given the results of the statistic analysis, the following recommendations are then made:

- Choosing start and stop time reasonably to avoid standby periods for machines with the exception for the oven, which needs a long heat-up time. This could all together save 387 kwh energy.
- Machines should be operated close to 75% rated capacity by using suitable machines or adjusting the system process, making machines working at peak efficiency could reduce about 469 kwh energy consumption.
- Utilities to correct voltage unbalance in the power supply should be installed, which could adjust the current unbalance to less than 10% in practice.

In addition, based on the discussion of the energy efficiency optimization, the job shop scheduling problem is investigated from the economic benefit aspect, which shows a £80 saving per day during the case study period. Therefore, the improved production process could maximise resource utilisation and minimise cost based on the commercial electricity tariffs.

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