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Review

Industrial energy systems in view of energy efficiency and operation control

Xiaohua Xia*, Lijun Zhang

Department of Electrical, Electronic and Computer Engineering, University of Pretoria, Pretoria 0002, South Africa

A R T I C L E I N F O

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A B S T R A C T

Energy efficiency improvement of industrial systems through the application of demand side management (DSM) techniques is discussed. In particular, a unified classification of efficiency of energy systems, namely performance efficiency, operation efficiency, equipment efficiency and technology efficiency (POET), is reviewed and further discussed to facilitate effective use of DSM methods in a selection of energy-intensive industrial processes. The operational level efficiency improvement is then focused on and the corresponding modelling and control by model predictive control (MPC) approach are presented. The modelling process is generalised to cater for a number of industrial processes. Robustness and convergence of MPC method when applied to periodic industrial processes are elaborated. The relationship between control and the POET is outlined thereafter to link the two such that one can make use of the POET concept to guide the controller design. Finally, case studies are provided to demonstrate the effectiveness of the approaches presented.

1. Background

The world has been actively seeking for less energy-intensive and renewable technologies for decades to promote sustainable and environmentally friendly development. The energy challenges faced by the world since 1970s were the driving forces of energy-efficient operation of many energy consuming processes[1]. Although some argue that improving energy efficiency will lead to more affordable energy and its use, thus resulting in more consumption (Herring, 2006), the fact that energy efficiency improvement ensures less consumption per activity or production unit is of great value for a greener society.

Among other solutions, energy efficiency improvement through demand side management (DSM) technologies has shown its effectiveness in reducing energy usage in various applications. In particular, it is known that the industrial sector consumes about 37% of the worlds total delivered energy (Gellings, 1985), reducing consumption by this sector thus will make a big difference in terms of the world's energy scenario.

DSM programs seek to reduce the gap between power supply and demand broadly by conservation, load management, fuel substitution, load building and self-generation, among which energy conservation, commonly known as energy efficiency (EE), and load management (LM) are the most popularly used methods in the industrial sector (Abdelaziz, Saidur, & Mekhilef, 2011). The LM approach aims to reduce electricity demand at peak periods by means of monetary incentive to shift load to off-peak periods, e.g., in the form of a time-of-use (TOU) tariff or a demand response programme (Eissa, 2011; Saini, 2004). The EE approach aims to reduce overall electricity consumption by installing energy efficient equipment and/or optimising industrial processes.

Numerous application of DSM techniques to various industrial systems were reported in the literature. For instance, DSM technique was introduce to reduce energy consumption and the associated cost for industrial and domestic pumping systems (van Staden, Zhang, & Xia, 2011; Zhang, Xia, & Zhang, 2012, 2014; Zhuan & Xia, 2013a,b). The operation of heavy-trains was modelled (Chou, Xia, & Kayser, 2007) and controllers were designed to optimise the safe and energy-efficient operation of the trains (Chou & Xia, 2007; Xia & Zhang, 2011; Zhang & Zhuan, 2014a, 2015; Zhuan & Xia, 2006, 2007, 2008, 2010). Operation modelling and optimisation for hybrid solar power systems were studied in (Tazvinga, Xia, & Zhang, 2013; Tazvinga, Zhu, & Xia, 2014, 2015; Wu, Tazvinga, & Xia, 2015; Zhu, Tazvinga, & Xia, 2015). Applications of DSM technologies, including modelling, energy management and operation control, to mining processes, such as conveyor belts (Mathaba & Xia, 2015; Shen & Xia, 2014; Zhang & Xia, 2010; S. Zhang & Xia, 2011), rock winders (Badenhorst, Zhang, & Xia, 2011), crushers (Numbi & Xia, 2015, 2016; Numbi, Zhang, & Xia, 2014), ventilation systems

* Corresponding author.
E-mail address: xxia@up.ac.za (X. Xia).

[1] The History of Energy Efficiency. Alliance Commission on National Energy Efficiency Policy, 2013.

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(Chatterjee, Zhang, & Xia, 2015), coal washing processes (Meyer & Craig, 2010; Zhang & Xia, 2014; Zhang, Xia, & Zhang, 2015), etc., to save energy and cost were studied. In addition to applications to the demand side, similar techniques were also reported in the maintenance of power plants (Ekpenyong, Zhang, & Xia, 2012), and economic generation dispatching for power plants (Elaiw, Xia, & Shehata, 2012a; 2013; 2012b; Nwulu & Xia, 2015a,b; Xia & Elaiw, 2010; Xia, Zhang, & Elaiw, 2011). The list can be expanded extensively because of the abundance of such applications.

There is a need to present a general framework to guide the DSM activities for industrial systems to facilitate the identification of potential EE interventions by DSM techniques and to guarantee the effectiveness of the DSM measures employed. In this paper, a review of a unified classification of energy efficiency in energy systems to aid energy audit and EE measures design is presented. In addition, the optimal operation of industrial systems is discussed in detail from optimisation and model predictive control (MPC) perspectives.

Section 2 gives an overview of the unified energy efficiency classification in terms of performance efficiency, operation efficiency, equipment efficiency and technology efficiency (POET). Section 3 discusses the optimal operation of industrial processes. The relationship between POET and operation control is discussed in Section 4. Some case studies are provided in Section 5 to demonstrate the convenience and effectiveness of the application of the presented approach. Finally, Section 6 concludes this paper.

2. POET analysis of energy systems

Generally, DSM methodologies' application to industrial systems falls into the aforementioned two categories, namely EE and LM. In 2010, a unified classification of efficiencies in an energy system was proposed by the Centre of New Energy Systems at the University of Pretoria (Xia & Zhang, 2010b, 2011; Xia, Zhang, & Cass, 2012). This classification was then adopted by the South African National Hub for the Postgraduate Programmes to develop EE curricula and design national EE intervention policies and guidelines[2]. The introduced concept categorises efficiency of an energy system into four sub-efficiencies in terms of POET. The POET approach establishes an general framework to conduct energy audit, to identify energy saving potentials and to plan energy efficiency improvement interventions. A brief discussion of the POET framework is presented in the following sections.

2.1. POET components of energy efficiency

Technology efficiency is discussed first because technology dictates the possible efficiency rates in all other components.

Technology efficiency is a measure of efficiency of energy conversion, processing, transmission, and usage; and it is often limited by natural laws such as the energy conservation law. Technology efficiency is often evaluated by the following indicators: feasibility; life-cycle cost and return on investment; and coefficients in the conversing/processing/transmitting rate (Weston, 1992).

Technology efficiency is characterised by its novelty and optimality. On the one hand, ground breaking and feasible novel technologies often defeat older peer technologies and occupy the market quickly. On the other hand, these novel technologies always challenge optimality through the pursuit of scientific limits and the quest for possible extremes.

Equipment efficiency is a measure of the energy output of isolated individual energy equipment with respect to given technology design specifications. The equipment is usually considered being separated from the system and having little interactive effect to other equipment or system components. Equipment efficiency is evaluated by considering the following indicators: capacity; specifications and standards; constraints; and maintenance.

Equipment efficiency is specifically characterised by its standardisation and constant maintenance. The most important aim of equipment efficiency is to minimise the deviations of the actual equipment parameters to the given design specifications. The difference between equipment efficiency and technology efficiency is easily illustrated by considering the compact fluorescent lights (CFL) example: The study on the improvement of CFL technology to provide more efficient lighting facilities forms part of the category of technology efficiency improvement, while replacing incandescent lights with CFLs is part of the equipment efficiency improvement category.

Operation efficiency is a system wide measure evaluated by considering the proper coordination of different system components. This coordination of system components may consist of the physical, time, and human coordination parts. These parts can again be indicated by sizing, matching, skill levels, and time control of these system components. Operation efficiency has the following indicators: physical coordination indicators (sizing and matching); time coordination indicator (time control) (Middelberg, Zhang, & Xia, 2009); and human coordination. In particular, sizing of one system component is to consider the relationship of this component with respect to the rest components of the system, thus sizing of the system component is an operational issue comparing with the capacity consideration in the equipment efficiency context.

Performance efficiency of an energy system is a measure of energy efficiency which is determined by external but deterministic system indicators such as production, cost, energy sources, environmental impact and technical indicators amongst others. It is worth noting that sometimes these performance efficiency indicators are contradictory or in competition with each other. An energy system will be expected to maximise the production and at the same time minimise cost and emission. Therefore the performance efficiency can only be improved when certain trade-offs among different indicators are made. The sustainability of the energy system can be reached if the engineering indicators (e.g., sources, technical indicators) do not compete with those socio-economic indicators (e.g., production, cost, environmental concerns). Apart from the indicators listed above, all the performance, operation, equipment and technology efficiencies are affected by technical, human, and time factors. For example, human wisdom and the corresponding decisions are often deterministic to technology efficiency; and a time-of-use electricity tariff will stimulate the improvement of performance efficiency.

The four POET efficiency components may not have clear-cut boundaries, they may also exist at micro-level underneath a more visible macro-level, exhibiting a multi-layer structure.

2.2. Implications of POET

Technology efficiency is a deciding factor to equipment efficiency, operation efficiency, and performance efficiency (see Fig. 1). The deterministic relationships can be used to further decompose the POET components. In Fig. 1, equipment efficiency has two parts E1 and E2. E1 represents the differences between output energy and specification, while E2 denotes the efforts such as maintenance which can help the equipment to keep its specifications. E1 is directly affected by technology efficiency but E2 is not.

[2] Eskom Energy efficiency and Demand Side Management Program Evaluation Guideline Proposal–A POET Based Measurement and Verification Approach from the Engineering, Environmental, Social, and Economic Aspects, 2011.

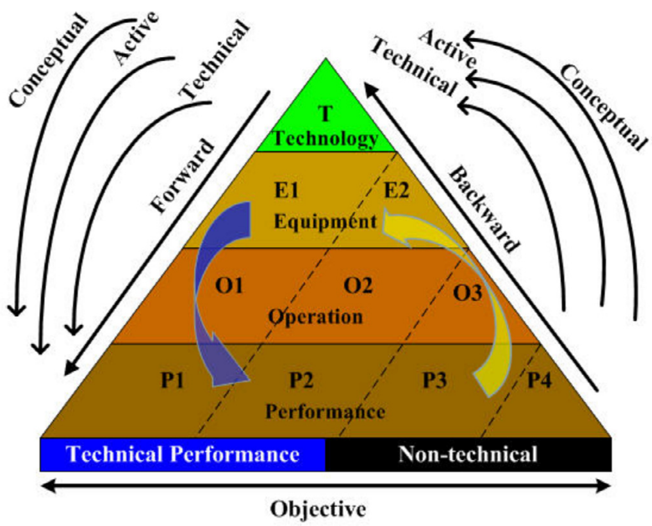

Fig. 1. POET components.

Similarly operation efficiency is divided into three blocks O1, O2 and O3. O1 is the part determined by technology efficiency and thus impacted by equipment efficiency. O2 is the part determined by E2 in equipment efficiency, and it can be the relevant system component coordination for equipment maintenance, the time-related operational strategies for efficiency improvement, or other factors determined by E2. O3 is the part in operation efficiency which is not affected by equipment efficiency and technology efficiency. An example for O3 is the skill levels of the human operators.

Performance efficiency has four parts P1, P2, P3, and P4. P4 is the energy losses which includes theft, leakage and line losses, and is not determined by OET. P1 is the energy performance part which is determined by O1, and thus also by equipment and technology efficiencies. P2 denotes the part determined by P2 and E2, and it can often be the time performance, or the 'power' of a system. If E2 represents the maintenance efficiency of a pumping system, then block O2 can be the optimal scheduling of existing pumps for a maintenance plan, and P2 can be the obtained maintenance timetable which implies the relevant cost for maintenance and possible benefits brought by the maintenance activity. P3 is the operation efficiency part determined by O3, and it can be the soft kWh resulted from the operators skills in O3 in many cases.

Some of the blocks in Fig. 1 can also be regrouped and understood in the following way. Blocks Technology (T), E1, O1, and P1 are the energy group since all of them are determined by the corresponding energy technology. Blocks E2, O2, and P2 are often time related and can be called time planning. Blocks E2, O3, and P4 often denote the behaviour changes of end users in the energy system. Blocks P1 and P2 are determined by technical factors such as the technology in an energy equipment, advanced optimisation of system component coordination, etc. Blocks P3 and P4 are determined by non-technical factors such as the skill training for energy system operations, energy waste/loss reduction, etc.

The POET decomposition and grouping become extremely interesting and useful when they are used to plan and prioritise energy management activities, projects, programmes, and human support and interventions. For instance, a 'quick win' in detecting the non-technical losses is usually the first target. 'Low hanging fruits' are normally picked up in addressing behaviour change. Some existing DSM policy programmes quantify energy saving potentials in different categories and groups (Skinner, 2012).

Energy management activities consist of ways of putting these energy efficiency components together so that sustainability is achieved. There are roughly two ways of doing so: the forward method and the backward method. The forward method is a feed forward from technology efficiency to performance efficiency. This entails starting from a technology, then designing the corresponding equipment, finding out suitable operations, and reaching certain performance efficiency levels. The backward method is a feed backward from performance efficiency to technology efficiency. This entails starting from practical demand or market analysis in performance efficiency, then investigating the operations, designing equipment, and later upgrading the practices into technology and theory. It is worth noting that the forward method is a prescriptive one since technology prescribes the other energy efficiency components; while the backward method is a driving one which provides market driven forces for the development of the corresponding technology.

When moving forward from technology efficiency to performance efficiency, usually an energy audit (Thumann & Younger, 2003) process will be done. This initial energy audit process is to profile energy consumption and to identify the energy saving opportunities. Through this process a rough objective or target such as possible percentage of energy savings or energy efficiency improvement can be obtained. After that, one can move backward from performance to technology efficiency to perform energy system planning (Owens, 1986) consisting policy support and the organisation structure. The planning will eventually impact the implementation of technology efficiency. This cycle is called a conceptual cycle for the purpose of this discussion.

Thereafter, one may start again from the improved technology efficiency and move to performance efficiency. This process involves an active audit to be done. The active energy audit makes use of more detailed energy information to further explore and consolidate sectoral or categorial specific energy saving opportunities. Upon completion of the active audit stage, an active objective with targets and possible margins will be obtained. From this active objective/target, one may again go back to performance efficiency, and finally reach technology efficiency. This backward process is now in an active planning stage by listing, putting together, prioritising and eventually implementing technical options and alternatives. At the completion of the active planning stage realistic energy efficiency improvement will be reached. This cycle is called an active cycle, and the energy management can be continued to go into a new cycle which is termed the technical cycle. More technical issues such as metering, baselining, monitoring, evaluating, calculating energy usage, verifying saving targets; and making dedicated engineering comparison, combination, and optimisation of technical solutions, are considered in the energy efficiency improvement in this technical cycle. One can continue the procedures for further energy efficiency improvement or to monitor the implementation as time goes by. These strategic cycles provide indications of the financial viability for the energy efficiency improvement.

The strategic cycles in energy management must be supported by engineering cycles which can be represented by the cycles inside the triangle in Fig. 1. In an engineering cycle, one starts from technology efficiency and moves to performance efficiency to begin the energy modelling process (Owens, 2006), then a baseline is obtained. From this baseline, one moves backward through the energy optimisation process (Owens, 2006). When moving forward, an energy audit is usually required. This auditing process can also be guided by the POET structure and categorised into conceptual audit, active audit and technical audit as demonstrated by Xia and Zhang (2010a). Applications of such auditing process to buildings and industrial processes have been discussed in (Xia & Zhang, 2010a; Xia et al., 2012). When moving backwards, the POET can be used to guide the controller design because of its close relationship to control systems as shown in (Xia & Zhang, 2010b, 2011).

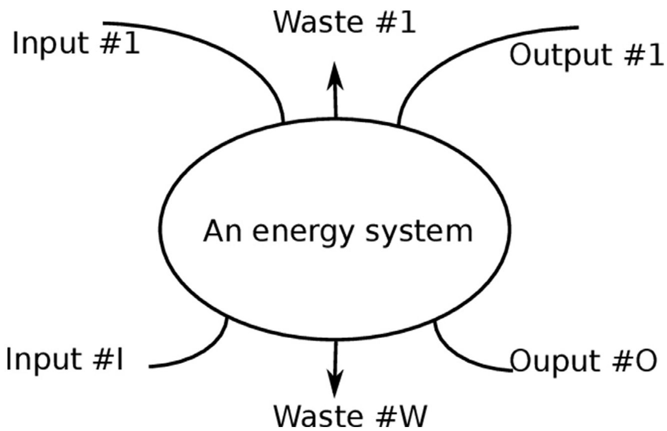

Fig. 2. Representation of a general energy system.

This engineering cycle can also be repeated, and it is often used to provide a technical viability analysis for the energy system. The support of engineering cycles is the third criterion for sustainability.

The engineering cycles embody systematic understanding of the energy products, processes and programmes, they are therefore dealt with in specialised disciplines. The following sections will focus on discussions from control engineering perspective.

3. Operation control of industrial systems

According to Xia and Zhang (2010b), operation efficiency is a system wide measure which is evaluated by considering the proper coordination of different system components. As detailed in the previous section, the coordination of system components consists of the physical, time, and human parts. It is usually difficult to model the human coordinations in operation efficiency, as discussed by Ekpenyong, Zhang, and Xia (2015), therefore we will focus on the physical and time coordination indicators in the following discussion. In DSM approaches, the purpose of energy efficiency improvement is usually to reduce energy consumption and the associated cost while maintaining the service level of the existing process. In order to achieve this target, an optimisation problem, taking into account all constraints and properly chosen objective functions, must be formulated. The modelling of system dynamics, objective functions and constraints are presented under this section, followed by a model predictive control (MPC) approach to solve the operation control problem formulated.

3.1. System modelling

Mathematical modelling of the dynamics of the underlying physics of the process is a prerequisite for the establishment of an operation optimisation or control problem. Without loss of generality, let's consider an energy system that takes energy inputs from I sources and delivers O outputs sketched in Fig. 2. The energy provided by the sources is converted to different forms and part of it is delivered to the outputs. The remaining part, however is dissipated by the process itself as waste through different channels, from 1 to W, as shown in Fig. 2.

At system level, the process can be modelled according to energy balance as

$$\sum_{i=1}^{I} E_i^{in}(t) = \sum_{j=1}^{O} E_j^{out}(t) + \sum_{k=1}^{W} E_k^{loss}(t), \tag{1}$$

where E_i^{in} denotes the energy contribution of source i, E_j^{out} denotes the energy delivered to the jth output and E_k^{loss} denotes the energy waste because of the kth energy consuming component.

The system level model describes the steady-state energy balance of an energy system. At component level, more detailed dynamical model can be built considering the time dynamics of the components, which is usually described by differential or difference equations. In the modelling process, according to the nature of the process and the objective of the problem at hand, physical laws such as mass flow balance (Meyer & Craig, 2010), Newton's laws (Xia & Zhang, 2011), etc., are usually used.

3.2. Objective functions

The energy consumption of the process is determined by the required output from the system and the efficiency, or equivalently loss, of the process itself. Let $u = [u_1, u_2, \ldots, u_N]$ represent the set of manipulated parameters of this process (these are usually the energy governing parameters), the objective functions can be chosen as the energy consumption and the energy cost as follows

$$J_1 = \int_0^T \sum_{i=1}^{I} P_i(u(t))dt, \tag{2}$$

$$J_2 = \int_0^T \sum_{i=1}^{I} p_i(t)P_i(u(t))dt, \tag{3}$$

where $P_i(u(t))$ represents the power drawn by the process from the ith energy source at time t. $[0, T]$ specifies the operation period of the process. $p_i(t)$ represents the cost of energy from source i at time t. The two objective functions J_1 and J_2 represent the energy consumption and energy cost of the process, respectively.

3.3. Constraints

From operational point of view, energy systems are usually subject to constraints consisting of its dynamics, operational limits and boundaries.

3.3.1. System dynamics

System dynamics is the result of system modelling. The model obtained forms an equality constraint for the operation optimisation problem. For a specific problem, the system dynamics needs to be built according to the underlying physics and can usually be represented by, say, differential equations as follows:

$$\dot{x} = f(x, u), \tag{4}$$

where $f(x, u)$ represents the dynamics of the system in terms of state variable x and the manipulated variable u.

Other dynamical processes are the simple modelling of an integrator of the following discrete form:

$$x(k+1) = x(k) + u(k). \tag{5}$$

3.3.2. Operational constraints

Operational constraints represent the requirements of the operation of the process. The most commonly seen operational constraints are the logic correlations and service correlations (Xia & Zhang, 2015). The logic correlation exists for a process, in which the status of different components depend on each other. Take an on/off operation problem for example. If the on/off status of one component depends on that of another component inside the process, there is a logic correlation between those components. A mathematical expression must be built to represent this correlation. Let $u_i(t)$ denote the on/off status of components, which is defined as:

$$u_i(t) = \begin{cases} 1, & \text{if the } i\text{th component is on;} \\ 0, & \text{if the } i\text{th component is off.} \end{cases}$$

Also let

$$sgn(x) = \begin{cases} 1, & \text{if } x > 0; \\ 0, & \text{if } x = 0; \\ -1, & \text{if } x < 0. \end{cases}$$

The logic correlation can be interpreted in four different cases of the correlation. In case $u_j(t_b)$ must be in the off status if $u_i(t_a)$ is in the switched on status, the constraint is equivalent to:

$$(\mathrm{sgn}(u_i(t_a)) + 1)(\ \mathrm{sgn}(u_j(t_b)) + 2) \neq 6. \tag{6}$$

In case $u_j(t_b)$ must be in the on status if $u_i(t_a)$ is in the switched on status, the constraint is equivalent to:

$$(\mathrm{sgn}(u_i(t_a)) + 1)(\ \mathrm{sgn}(u_j(t_b)) + 2) \neq 4. \tag{7}$$

In case $u_j(t_b)$ must be in the on status if $u_i(t_a)$ is in the switched off status, the constraint is equivalent to:

$$(\mathrm{sgn}(u_i(t_a)) + 1)(\ \mathrm{sgn}(u_j(t_b)) + 2) \neq 2. \tag{8}$$

In case $u_j(t_b)$ must be in the off status if $u_i(t_a)$ is in the switched off status, the constraint is equivalent to:

$$(\mathrm{sgn}(u_i(t_a)) + 1)(\ \mathrm{sgn}(u_j(t_b)) + 2) \neq 3. \tag{9}$$

To meet special process or service requirements, some system components are often requested to be switched on simultaneously for a minimum time duration within a given period. This requirement is equivalent to request each of these components to be switched on for a minimum time duration at the given period. Assume that the ith component must be switched for at least a duration of ΔT within the period $[t_1,\ t_2]$. This requirement can be formulated as the following inequality: $\int_{t_1}^{t_2} \mathrm{sgn}(u_i(t))\mathrm{d}t \geq \Delta T$ There are also other types of process and service correlations. For instance, the part being manufactured must go through a certain sequence of difference processes in a batch production system. The corresponding constraints need to be worked out according to specific requirements.

3.3.3. Boundary constraints

There are often boundary constraints for some intermediate variables. This type of constraints usually include physical limits and performance targets. Examples of physical limits include the volume of a certain matter inside a container in the system, which is bounded by the capacity of that container, the rate of change of actuator actions, which is limited by their characteristics, etc. For target limits, an operation optimisation intervention is usually guided by a pre-determined target. For example, if the purpose is to achieve 10% of energy consumption reduction, then the target constraint can be written as

$$\frac{\text{Actual consumption}}{\text{Baseline consumption}} \times 100\% \leq 90\%.$$

These constraints can usually be written as a function of the manipulated variables $u_i(t), i = 1, \cdots, N$, according to relevant physical dynamic processes. Generally, the following inequality constraint is obtained:

$$\lambda(u) \geq 0. \tag{10}$$

The above mathematical modelling provides a summary for those frequently met modelling problems of energy systems. However, due to the complex nature of various industrial processes and service requirements, there will be much involved cases where none of the above derived models is directly applicable, and further analysis on the corresponding energy systems must be done.

3.4. Operation control using MPC

The optimisation model obtained in the preceding subsections, the equations from (1) to (10), is an optimal control model with control variable u.

Various methods have been employed to solve this type of control problem in the literature. Among those methods, MPC has shown its advantage mainly because of its robustness and ability to handle constraints in the controller design process, which are highly desirable for the control of industrial processes.

In an MPC approach, the problem is first discretized into discrete time instances by a sampling period Δt. Suppose the current time is $k\Delta t$, then the MPC solves a local optimisation problem over a moving optimisation period $[k\Delta t,\ (k+N_p)\Delta t]$. To simplify notation, this optimisation window will be denoted as $[k,\ k+N_p]$ in the following context and k will be used to denote the present time. With these notations, a local version of the discretized objective functions shown in (2) is shown below.

$$\begin{aligned} \min\quad & J_1(U_k) = \sum_{k=1}^{N_p}\sum_{i=1}^{I} P_i(U)\Delta t, \\ \min\quad & J_2(U_k) = \sum_{k=1}^{N_p}\sum_{i=1}^{I} p_i(k)P_i(U)\Delta t, \\ \text{s.t.}\quad & F(U_k) = 0, \\ & G(U_k) \leq 0, \end{aligned} \tag{11}$$

where $U_k = [u(k|k), u(k+1|k), \ldots, u(k+N_c-1|k)]$ is the control variable, in which N_c denotes the control horizon, $[k, N_c-1]$. $p_i(k)$ is the cost of energy from the ith source during the kth interval. The equality constraint $F(U_k) = 0$ is the discrete form of the system dynamics derived from (4), which is usually simplified to a steady-state equation around the operating points of the system, similar to the energy balance Eq. (1). This can be done for industrial energy systems because they are constantly consuming energy for a long duration around their steady state. The inequality constraint $G(U_k) \leq 0$ is the discretized form of the operational and boundary constraints discussed in Sections 3.3.2 and Section 3.3.3.

Although only performance efficiency indicators are explicitly shown in the objective functions of (11), other efficiencies are also considered by the optimisation because indicators of those efficiencies are implicitly reflected in the performance efficiency.

This problem is solved iteratively with the moving horizon $[k\Delta t, (k+N_p)\Delta t]$ for $k = 1, 2, \ldots$ till the ending time of the operation. After the solution is obtained, the first element of U_k, $u(k|k)$ is implemented over the time period $[k, k+1)$. At the end of the time interval $[k, k+1)$, initial values are updated according to real time measurements, and the above problem is re-solved over the time interval $[k+1, k+1+N_p]$ for the variable U_{k+1}, which is defined in the same way.

3.5. Robustness of MPC

As discussed in many classical textbooks and academic papers, such as Allgöwer and Zheng (2000); Camacho and Bordons Alba (2007); Garca, Prett, and Morari (1989); Grüne and Pannek (2011); Qin and Badgwell (2003), closed-loop MPCs inherently possess the property of robustness against modelling uncertainties and external disturbances. This is further evidenced by the fact that MPC is one of the most used control methods in industrial and commercial systems (Qin & Badgwell, 2003). In particular, application of MPC to address problems raised from energy systems has been studied extensively with a great success. The disadvantage of MPC though is the lack of stability. Convergence of MPC is proved in rare cases under very strict conditions. This hinders the application of MPC to processes to which stability is pivotal.

However, it will be shown in the following subsection that the convergence and robustness of MPC when applied to a class of industrial systems can be theoretically proved, which guarantees the stability for such processes.

3.6. Application of MPC to periodic processes

Most industrial processes repeat themselves after a certain period, such as 24 hours. For example, both the operation of pumping stations (van Staden et al., 2011; Zhuan & Xia, 2013b) and dynamic economic dispatching (Xia et al., 2011) have a operating cycle of 24 h. The results obtain by MPC according the periodically changing operating conditions are usually implemented repeatedly in view of the periodic invariant characteristics of the processes.

However, there may have certain interactions between the two consecutive periods of the process that make direct implementation of the results obtained by MPC for one period impossible. The ramp rate violation when periodically applying the MPC results to the dynamic economic dispatching problem discussed by Xia et al. (2011) demonstrates this possibility. This is also termed as turnpike phenomenon in studies such as Dorfman, Samuelson, and Solow (1958); Faulwasser and Bonvin (2015); Faulwasser, Korda, Jones, and Bonvin (2014).

To resolve this problem, the original optimal control problem can be reasonably extended to include extra constraints representing the interactions of the process variables over more than one cycle of the operation to *perfect* the original problem such that the solution to the extended problem by MPC can be implemented repeatedly.

For simplicity, weighted average method can be used to reduce the original multi-objective optimisation problem defined in (11) to a single objective optimisation problem. The popularly used weighted average method cannot guarantee to find the complete set of solutions to the original multi-objective problem (Pareto Front), it, however, is useful to find a solution to the problem with specified weighting factors, which are usually selected carefully according to the trade-offs made among the objectives. This provides a way for decision makers to give instructions to the optimisation procedure, which is highly desirable in industrial applications. The resulting single objective control problem, over one operating cycle of the process ($[k,\ k+p]$), can be denoted by:

$$\begin{aligned} \min\ & J_k(z[k+1|k]),\\ \text{s.t.}\ & H_k(z[k+1|k]) \le 0, \end{aligned} \tag{12}$$

where p is the period of the periodic process, $z[k+1|k] = [u[k|k]^T, \dots, x[k+p-1|k]^T]^T$ is a column vector consists of the predicted control variables. J_k is the weighted sum of J_1 and J_2 in (11) and H_k is the lumped constraints from F and G in (11). Both J_k and H_k are convex and smooth functions that satisfy the periodic invariant property:

$$\begin{aligned} & J_k(u[k+1], \dots, u[k+p])\\ &\quad = J_{k+1}(u[k+1], \dots, u[k+p], u[k+1]),\\ & H_k(u[k+1], \dots, u[k+p])\\ &\quad = H_{k+1}(u[k+2], \dots, u[k+p], u[k+1]). \end{aligned}$$

By introducing a new set of periodic invariant constraints

$$H'_{k+1}(z[k+1|k]) \le 0,$$

a perfection of the original problem can be obtained as:

$$\begin{aligned} \min\ & J_k(z[k+1|k]),\\ \text{s.t.}\ & H_k(z[k+1|k]) \in \Omega_k, \end{aligned} \tag{13}$$

where Ω_k is a nonempty set of constraints defined by

$$\begin{aligned} \Omega_k =& \Big\{ z[k+1|k] : H_k(z[k+1|k]) \le 0,\\ & H'_{k+1}(z[k+1|k]) \le 0 \Big\}\\ =& \Big\{ z[k+1|k] : H_{k+ip+1}(u[k+1], u[k+2], \dots,\\ & u[k+p]) \ge 0, H_{k+ip+2}(u[k+2], u[k+3], \dots,\\ & u[k+p], u[k+1]) \ge 0, H_{k+ip+p}(u[k+p],\\ & u[k+1], \dots, u[k+p-2], u[k+p-1]) \ge 0,\\ & \text{for all } i \Big\} \end{aligned}$$

MPC solution to this extended problem can then be implemented over the complete operation interval of the process under consideration. The convergence and robustness of the MPC solution to this problem are proved by Zhang and Xia (2011a) and thus not provided here. This proof provides theoretical foundation for the application of MPC to periodic industrial processes.

4. Relationship between control system and POET

There is a strong relationship between the energy-efficient operation control of industrial systems and the POET concept. Studies on the minimal fuel problem in classical optimal control theory (Heinen, 1976; Naidu, Hibey, & Charalambous, 1990) are often connected to the problem of minimal energy consumption of certain energy systems. The resemblance between the POET classification and control systems is discussed at the disciplinary level. In a control system, there are four important components which are used to obtain an optimal control for a system. In fact, the purpose of control theory is to find a good controller for a physical system, therefore the first important component in a control system is to identify the objectives of control as shown in the modelling section of this paper. The objective functions are usually determined by external factors to be controlled, thus the objectives can be used as indicators to measure the performance efficiency.

The second component is to model the system dynamics. This is to model the physical interactions and constraints of different system components by deep understanding on the technical phenomenon. This component is correlated to the basic features of technology efficiency. Technology can generally be represented by the approach taken for system modelling.

The third component is operation planning which is often determined by the relations and coordinations of internal system components. This can be done in an open loop nature such as the plant wide automation of an industrial system, as well as a closed-loop nature such as system MPC problem formulated in the preceding subsection. Both of these open loop and closed-loop strategies are essential issues in operation efficiency.

The fourth component is the implementation of controllers. This is expected to be done as specified in the physical realisation via actuator devices and the corresponding lower level controllers, hence it corresponds to the equipment efficiency.

A more in depth analysis of the connection between control system and energy efficiency is done in (Xia & Zhang, 2011) with the help of a train transportation system.

5. Case studies

The operation of industrial systems corresponds to the operation efficiency of the POET classification. Three case studies are presented here in terms of the physical coordination and time coordination indicators, namely, optimal component sizing, matching, and timing control. Although human coordination is an essential part of the operation problem because human skills are involved in all levels of operation of industrial systems, it is not covered in

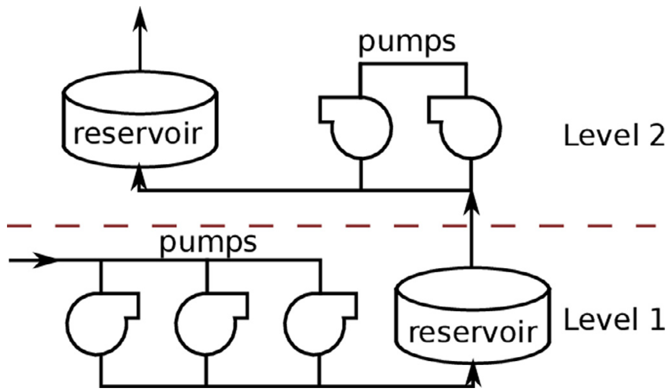

Fig. 3. A multi-level pumping system.

this paper because of the lack of study in this aspect (Ekpenyong et al., 2015).

5.1. Component sizing

An important step toward an efficient system, according to the POET framework, is the proper sizing of equipment to its operation requirements. Optimal sizing of a pumping system was presented by Zhang et al. (2012). A multi-level pumping system as shown in Fig. 3 was considered, and the optimal sizing problem was formulated into an optimisation problem with the following objective function:

$$\min_{u_{r,i},q_r} \sum_{r=1}^{R_c}\sum_{i=1}^{I_c} p_i f_r(q_r)u_{r,i}\Delta t + M_{md}p_{md}, \quad (14)$$

where the decision variables $u_{r,\ i}$ and q_r represent the on/off status of the pump at the ith sampling interval and the capacity of the pump at the rth level, respectively. R_c is the total number of levels of the pumping system, I_c is the number of control intervals, p_i is the TOU electricity tariff, $f_r(q_r)$ denotes a function that computes the required input power for a given capacity at the rth level. Δt is the sampling period of the control. The term $M_{md}p_{md}$ denotes the maximum demand charge of the electricity used by the pumping system.

This problem is solved subject to constraints including the binary constraint on the on/off status of the pumping control variable $u_{r,\ i}$ and the boundary constraint on the capacity of the reservoirs defined by:

$$LB_r \le l_{r,i+1} = l_{r,i} + q_r u_{r,i}\Delta t - d_{r,i} \le UB_r,$$

where $l_{j,\ i}$ and $d_{r,\ i}$ denote the volumes of water inside and flowed out of the reservoir on the rth level during the ith sampling period. LB_r and UB_r represent the lower and upper bounds of the water inside the reservoir because of the capacity limit of the reservoir.

It is noted that the water volume balance equation in the above constraint is actually the steady-state model of the pump-reservoir system.

This problem was solved for each level, and an example under South African high demand season TOU tariff was solved with $d_{r,\ i}$ set to 70 m^3/h for all i and the LB_r and UB_r set to 500 m^3 and 1000 m^3, respectively. The optimal pump capacity was found to be 103.023 m^3/h, which allowed the pumping system to shift the entire load out of peak period to save energy cost.

There are many more examples on the application of DSM technique to optimally size system components. For instance, the optimal sizing of electrical energy storage systems for energy efficiency improvement (Berrada & Loudiyi, 2016; Schneider et al., 2015), optimal sizing of stand-alone hybrid PV system supplying remote areas (Ahmadi & Abdi, 2016; Fathy, 2016) and optimal sizing of components in electric vehicles for better energy management (Xu, Mueller, Li, Ouyang, & Hu, 2015), etc.

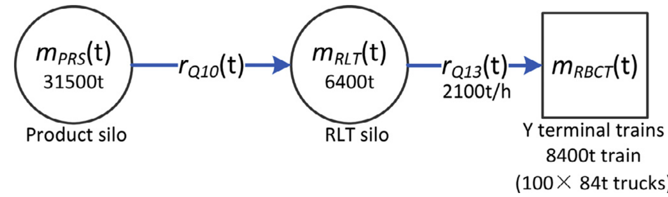

Fig. 4. Coal transport process in a colliery.

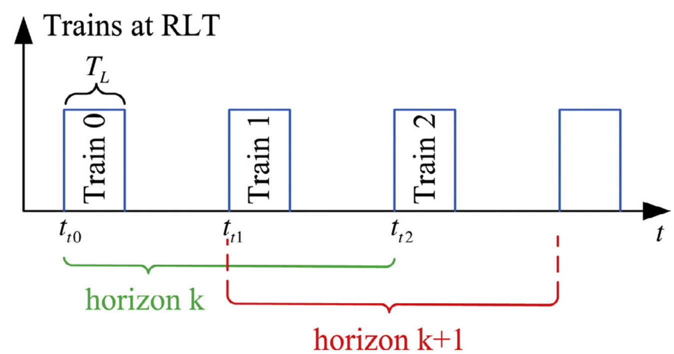

Fig. 5. Adaptive control horizon.

5.2. Matching control

The optimal load shifting control for a colliery studied by Middelberg et al. (2009) is a good example of matching control at the operation level. The problem is to optimally control the on/off status of a group of conveyor belts used to transfer coal from a large silo to a train terminal, where the coal is loaded to trains that transport export quality coal to export ports. This process is simplified and shown in Fig. 4, in which $m_{PRS}(t)$, $m_{RLT}(t)$ and $m_T(t)$ represent the mass of coal in the product silo, the rapid loading terminal (RLT) and the train, respectively. $r_{Q10}(t)$ and $r_{Q13}(t)$ denote the mass flow rate of coal in the two conveyor belts named Q10 and Q13, respectively.

The trains arrive at the loading terminal at discrete time intervals according to the train schedule. The control problem is formulated with the objective of minimising energy cost of the conveyor belts under TOU tariff.

In order to achieve the goal of cost minimisation for this system, the on/off schedule of the conveyor belts must match the schedule of the trains. Since the trains do not arrive at fixed time intervals, the control horizon is chosen to be adaptive in the sense that it extends over a period of two train arrivals, i.e., from the time of arrival of the current train (train 0) at time t_{t0} to the time of arrival of the second train after train 0, namely train 2 at time t_{t2}, as shown in Fig. 5.

Once train 1 of the kth control horizon arrives at time t_{t1}, this time becomes the initial time t_{t0} of the $k+1$th control horizon. The control horizon thus shifts forward each time a train arrives such that the control always optimises the operation of the conveyor belts for at least one extra train interval after the current one.

Because the operation of Q13 conveyor is determined by the train schedule, it must be running when there is a train needs to be loaded and it must be switched off when there is no train waiting for loading, its operation is thus not included in the optimal control problem. Therefore, this problem is finally formulated with the following objective function:

$$\min_{u_{Q10}} \sum_{k=1}^{N-1} P_{Q10} u_{Q10}(t_k) p(t_k) \Delta t, \qquad (15)$$

where $[0, N\Delta t]$ denotes the control horizon, where $N = \frac{t_2 - t_0}{\Delta t}$. P_{Q10} denotes the power consumption of the Q10 conveyor belt when it is running, u_{Q10} is the switch variable representing on/off status of the belt and $p(t_k)$ is the electricity price at the kth sampling interval.

The constraints for this problem are mainly the boundary constraints on the capacity of the RLT silo

$$0 \le m_{RLT}(t) \le m_{RLT}^{max},$$

where m_{RLT}^{max} is the maximum capacity of the RLT silo, and the $m_{RLT}(t_k)$ is obtained by the system dynamics

$$m_{RLT}(t_k) = m_{RLT}(t_{k-1}) + r_{Q10} u_{Q10}(t_k) - r_{Q13} u_{Q13}(t_k),$$

where r_{Q10} and r_{Q13} are the rated mass flow rates of the Q10 and Q13 conveyors, respectively.

Model predictive control method is used to solve this problem and results obtained over a period of five consecutive days in high demand season show 17% reduction of energy consumption during peak period, which translates to 46% reduction in the electricity cost, when compared to the existing operating strategy of the colliery (Middelberg et al., 2009).

Other examples of matching control include optimal matching of the physical coordination between braking and dragging forces of the heavy-haul trains in order to achieve desired performance in terms of energy efficiency, velocity tracking and operation safety presented in (Chou & Xia, 2007; Zhang & Zhuan, 2014a,b; 2015; Zhuan & Xia, 2006, 2007, 2008, 2010); the matching of power generation by diesel generators with respect to solar power output to provide a stable power supply to the end users in remote areas studied in Tazvinga et al. (2013, 2014, 2015); Wu et al. (2015); Zhu et al. (2015) etc. The economic power dispatching problem is also a matching problem which strikes for an optimal balance between the generator output and the end user demand (Elaiw et al., 2012a; 2013; 2012b; Nwulu & Xia, 2015a,b; Xia & Elaiw, 2010; Xia et al., 2011).

5.3. Timing control

An optimisation model for mine ventilation fan speeds developed by Chatterjee et al. (2015) is presented here as an example of operation control of industrial system in terms of the time coordination of the operation efficiency.

The potential for energy cost savings and actual energy savings by implementation of variable speed drives to ventilation fans in underground mines was investigated. The operation of ventilation fans was optimised taking into account the TOU tariff and the concept of ventilation on demand (VOD), i.e., air volume is adjusted according to the demand at varying times. Two problems, one for EE improvement and one for LM were studied by Chatterjee et al. (2015). For simplicity, only the EE improvement problem is presented in the following.

To find the optimal fan speeds that result in minimum energy cost, while adhering to the flow rate requirements, the problem objective function was chosen as

$$\min_{N_k(t)} \sum_{k=1}^{K} \sum_{t=1}^{T} P_k(N_K(t)) p(t) \Delta t, \qquad (16)$$

where K is the number of fans in the ventilation network, $p(t)$ is the electricity cost at time t, $P_k(N)$ is a 3rd order polynomial that describes the power of the fan k as a function of its speed $N_k(t)$. Δt is again the sampling period.

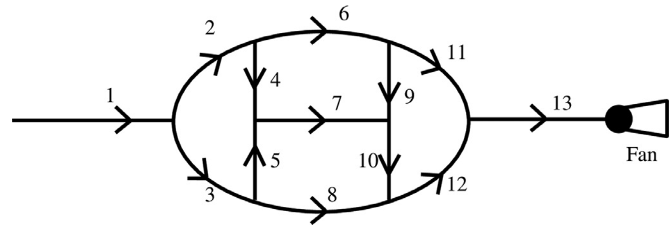

Fig. 6. Structure of the studied ventilation network.

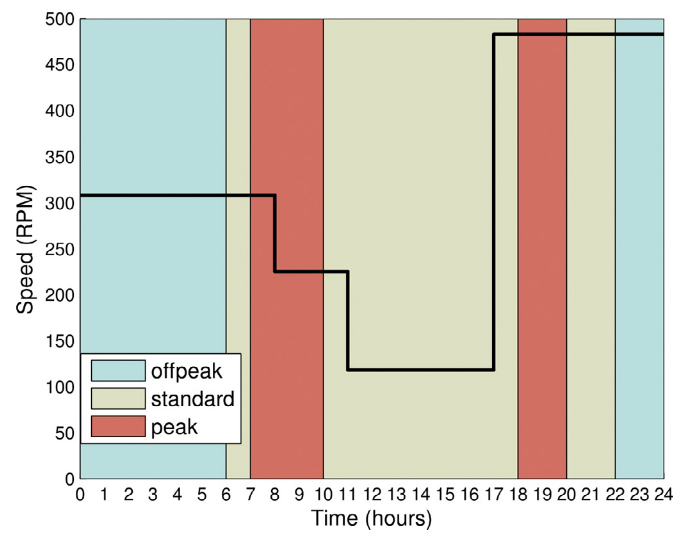

Fig. 7. Optimal fan speed.

This problem is subject to constraints including system dynamics described by following mass balance equation:

$$\sum_{j=1}^{n} B_{ij} Q_j(t) = 0, \text{ for } i = 1, \ldots, m,$$

where B_{ij} is the element of an $m \times n$ incidence matrix that describes the node-to-branch incidence, Q_j is the flow rate of branch j in the network. And the energy balance equation:

$$\sum_{j \in F} L_{pj} H_j(t) - \sum_{j=1}^{n} L_{pj} r_j Q_j^2(t) = 0, \text{ for } p = 1, \ldots, n_p,$$

where f is the branch number containing a fan, F is the set of branches containing a fan, $H_j(t)$ is the fan pressure in branch j at time t, which is derived from the fan laws. l_{pj} is an element of the path matrix $L = [L_{pj}]$, p is the path number, and n_p is the total number of paths.

The path matrix L is a $n_p \times n$ matrix that describes the branch-to-path incidence and defined by

$$L_{pj} = \begin{cases} 1, & \text{if path } p \text{ contains branch } j; \\ 0, & \text{if path } p \text{ doesn't contain branch } j. \end{cases}$$

The boundary constraint of this problem is defined by the VOD requirement as

$$Q_j^{min}(t) \le Q_j(t) \le Q_j^{max}(t),$$

where $Q_j^{min}(t)$ and $Q_j^{max}(t)$ are the minimum and maximum allowable airflow in branch j at time t.

The formulated problem was then solved for a ventilation network shown in Fig. 6 and the resulting optimal fan speeds and energy consumption of the fan over one day is shown in Figs. 7 and 8.

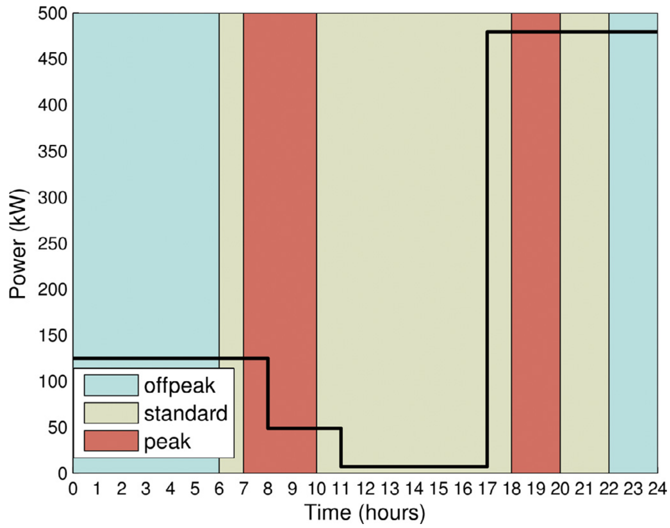

Fig. 8. Power consumption of the fan.

The optimised fan speed under the TOU tariff results in a daily energy cost of USD 431. Comparing this to a situation where the fan needs to be run at full capacity at all times to supply the maximum flow rate of 28.5 m^3/s to branches 7 and 8, the cost of energy would be USD 1015 per day. This leads to a cost saving of USD 584 per day, which adds up to USD 213160 cost saving per year (assuming the same cycle throughout the year). In terms of energy savings, keeping a constant speed leads to daily energy consumption of 11,499 kWh; whereas varying the speed results in the daily consumption to be 4540 kW h. This leads to daily savings of 6959 kWh, which translates to savings of 2,540,035 kWh per year.

Various examples of timing control for industrial systems can be found in the literature. For instance, the operation strategies for mining processes, such as conveyor belts (Mathaba & Xia, 2015; Shen & Xia, 2014; Zhang & Xia, 2010; S. Zhang & Xia, 2011), rock winders (Badenhorst et al., 2011), crushers (Numbi & Xia, 2015; 2016; Numbi et al., 2014), etc., in view of the TOU tariff, all fall into the category of timing control.

6. Conclusion

A review of the energy efficiency improvement technologies and their applications to industrial systems is presented. The review begins with a general classification of efficiency of energy systems in terms of technology efficiency, equipment efficiency, operation efficiency and performance efficiency (POET). The operation modelling and control by model predictive control method for industrial systems are then discussed. Convergence and robustness of MPC when applied to periodic industrial processes are reviewed to provide theoretical background for the application. After that, the correlation between the operation control and the POET framework is discussed. Case studies are provided at the end of the study to demonstrate the effectiveness of operation control approaches in improving energy efficiency of industrial processes with respect to the time and physical coordinations of the operation efficiency of the POET.

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