Identification of Microturbine Model for Long-term Dynamic Analysis of Distribution Networks

Xiandong Xu[a], Kang Li[a], Fengyu Qi[b], Hongjie Jia[b], Jing Deng[a]

[a] *School of Electronics, Electrical Engineering and Computer Science, Queens University Belfast, Belfast BT9 5AH, UK*
[b] *Key Laboratory of Smart Grid of Ministry of Education, Tianjin University, Tianjin, 300072, China*

Abstract

As one of the most successfully commercialized distributed energy resources, the long-term effects of microturbines (MTs) on the distribution network has not been fully investigated due to the complex thermo-fluid-mechanical energy conversion processes. This is further complicated by the fact that the parameter and internal data of MTs are not always available to the electric utility, due to different ownerships and confidentiality concerns. To address this issue, a general modelling approach for MTs is proposed in this paper, which allows for the long-term simulation of the distribution network with multiple MTs. First, the feasibility of deriving a simplified MT model for long-term dynamic analysis of the distribution network is discussed, based on the physical understanding of dynamic processes that occurred within MTs. Then a three-stage identification method is developed in order to obtain a piecewise MT model and predict electro-mechanical system behaviours with saturation. Next, assisted with the electric power flow calculation tool, a fast simulation methodology is proposed to evaluate the long-term impact of multiple MTs on the distribution network. Finally, the model is verified by using Capstone C30 microturbine experiments, and further applied to the dynamic simulation of a modified IEEE 37-node test feeder with promising results.

*Corresponding author
Email address: x.xu@qub.ac.uk,xuxiandong87@gmail.com (Xiandong Xu)

Preprint submitted to Applied Energy *September 15, 2016*

Keywords: Microturbines, model, identification, distribution network, dynamic analysis

1. Introduction

The integration of distributed energy resources (DERs) has significantly changed traditional design, operation, control and online management of electric power systems [1, 2]. Microturbines (MTs), which can provide both electrical and thermal energy, have been widely used as DERs in the electricity distribution network (hereafter referred to as distribution network)[3, 4]. Due to the advantages of high reliability, low emission, and high efficiency, an increasing number of MTs have been installed in the distribution network worldwide, and this has greatly enhanced interdependencies between the distribution network and natural gas network. Also, it has been observed that the gas network can significantly affect the operation of power systems through gas-fired generators [5]. Therefore, it is important to model the behaviours of various MTs, as well as to evaluate the impacts of large integration of MTs on the distribution network, in order to ensure a secure and reliable system operation.

In the study of energy systems, it is usually not possible to conduct large-scale physical experiments due to economic and security reasons. This promotes the popularization of using simulation as a tool to analyse the energy system behaviour under various scenarios [6, 7, 8]. In order to describe behaviours of the whole system, both network and coupling unit models are required for simulating the system. As one of the main energy networks in urban areas, distribution networks have been investigated by way of modelling [9], simulation [10], planning[11], scheduling[12], etc. Several packages have been developed to study their dynamic behaviours [13, 14, 15]. Dynamic load models, such as heat pumps [16] and air conditioners[7], are embedded in the packages. Considering the interactions between the electricity network and the gas network, a suitable dynamic MT model is required, so as to analyse its coupling function. However, the existing literature, with a few exceptions [17, 18], has mainly focused on the network analysis in steady states [6, 19, 20]. The dynamics of gas-fired generator and how they affect the interactions between the two networks are not well explored. In addition, in practice, the gas network information is usually not accessible to distribution network operators, which makes it difficult to analyse the impacts of natural gas pressure and other ambient conditions on distribution networks through MTs.

Due to the complex thermo-fluid-mechanical energy conversion processes [21], building MT models has become a significant but challenging work when analysing dynamic impacts of natural gas networks and MTs on the distribution network. One important direction of the MT modelling is to conduct mechanism analysis, using available packages in commercial software, such as DIgSILENT, PSCAD and MATLAB/Simulink [18, 22, 23, 24, 25, 26] For example, Rowen proposes a gas turbine mechanical model in [22], which describes the thermo-mechanical process of the MT prime mover. In [23], the correlation between the electro-mechanical and thermo-mechanical subsystems is modelled. The impact of MTs on the distribution network is analysed under a range of load conditions [24]. Further, dynamic behaviours of hybrid MT and other distributed generation system are investigated by using simulation studies and small-scale physical experiments [25]. As a prime energy source, natural gas is also critical for MTs' operation. Hence, natural gas flow is incorporated into the thermo-mechanical model of gas turbines in [26]. An improved MT model is developed to reflect the interactions between power and natural gas systems [18]. However, in practice, MTs may have different brands and capacities. The parameters and models are not the same for each MT. Moreover, some of the design parameters for MTs are confidential, and therefore are hardly accessible.

In order to handle the unknown parameters and the strong nonlinearity, another direction of the MT dynamic analysis is based on black-box approaches, where system identification techniques are commonly employed. By correlating input and output data, these techniques can help to build a simplified model of the complex process and to predict its behaviours without requiring much prior knowledge [27]. A variety of techniques have been proposed to describe the dynamics of gas turbines. These include polynomial models, such as nonlinear autoregressive moving average with exogenous inputs models and nonlinear autoregressive exogenous [28, 29], neural network models [30, 31, 32], and adaptive network-based fuzzy inference system [33]. These models are effective in correlating the fuel and mechanical power output for a specific MT, and are used in analysing the transient stability of distribution networks [9]. However, it is difficult for the electric utility to obtain the operation data of MTs owned by different third parties in distribution networks. Thus, system operators can hardly build identification models or estimate the internal states of the MTs, which play a key role in the security analysis of distribution networks.

In this paper, a simplified compact MT model is developed for the long-term dynamic analysis of distribution networks, considering different requirements and data availability for utilities and customers. The main contributions can be summarised as follows: 1) Dynamic characteristics of the MT are analysed in order to identify the model with the state space form and the piecewise method; 2) An electro-mechanical system model of the MT is derived using a three-stage subspace identification method to predict the MT power output under different operating conditions; 3) Based on the obtained model, a fast simulation method is proposed to the evaluate dynamic impact of MTs on the distribution network. Numerical examples show that the proposed model can capture MT power and heat output behaviours well over a wide operation range, and reflect the impact of multiple MTs on the distribution network.

The rest of this paper is organized as follows. Section II describes the feasibility of the model simplification and the three-stage model identification method. Section III presents a fast simulation method based on the proposed MT model. In Section IV, physical and numerical tests are performed to illustrate the accuracy and effectiveness of the proposed method. Finally, the conclusion is given in Section V.

2. Identification of the MT model

In this study, the MT model is developed for the long-term dynamic analysis of distribution networks with multiple MTs. To achieve this goal, the model should be able to capture dominant characteristics of the eletro-mechanical subsystem of the MT, while simple enough for large-scale applications. To trade-off model complexity versus accuracy, a novel modelling method for the MT will be proposed in this section, based on mechanism analysis of the MT and black-box approaches.

2.1. Dynamic characteristic analysis

This paper investigates a single-shaft MT which is widely used to supply both heat and power in local areas [34]. As illustrated in Fig. 1, the MT is composed of thermo-mechanical and electro-mechanical subsystems. The dynamic model of the MT can be expressed as

$$\begin{cases} \dot{x}_t = f_t(\dfrac{\partial x_t}{\partial p}, x_t, y_t, u, x_e, y_e) \\ \dot{x}_e = f_e(x_t, y_t, u, x_e, y_e) \\ \quad 0 = g(x_t, y_t, u, x_e, y_e) \end{cases} \tag{1}$$

where f_t and f_e represent thermo-mechanical and electro-mechanical subsystem models, and g links the two models algebraically. x_t and y_t represent thermo-

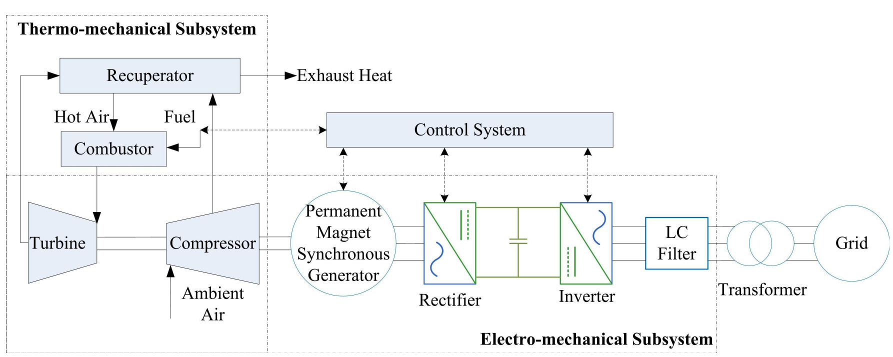


Figure 1: An overview of the MT configuration.

mechanical subsystem state and algebraic variables, including component temperature, fuel flow pressure, engine speed, exhaust exit temperature, flow rate, etc. p represent position variables. x_e and y_e stand for electro-mechanical system state and algebraic variables, including generator angle, converter control system states, generator power output, voltage, etc. u represents the control signal of the MT.

Due to the slow response actions, thermo-mechanical subsystem variables x_t can be seen as frozen during the electro-mechanical analysis process. Existing studies have shown that some state variables dominate the MT dynamics [35]. Based on the singular perturbation theory, the MT can model be further expressed as follow

$$\begin{cases} \dot{x}_{es} = f_{es}(x_t, y_t, u, x_e, y_e) \\ \epsilon\dot{x}_{ef} = f_{ef}(x_t, y_t, u, x_e, y_e) \\ 0 = g(x_t, y_t, u, x_e, y_e) \end{cases} \tag{2}$$

where ϵ is a small non-negative scalar. x_{es} and x_{ef} stand for slow and fast variables of the electro-mechanical subsystem. f_{es} and f_{ef} stand for slow and fast models of the electro-mechanical subsystem.

For the long-term dynamic analysis, the fast dynamics can be described by setting $\epsilon = 0$ in (2). The key dynamics of the electro-mechanical system can then be expressed as

$$\begin{cases} \dot{x}_{es} = f_{es}(x_t, y_t, u, x_e, y_e) \\ 0 = f_{ef}(x_t, y_t, u, x_e, y_e) \\ 0 = g(x_t, y_t, u, x_e, y_e) \end{cases} \tag{3}$$

2.2. State space model and system identification

In normal operating states, the engine speed of MTs is usually operated above a certain range in order to ensure high efficiency. Also, it has been demonstrated that the electro-mechanical system shows a good linearity in the operating range [35]. Therefore, it is reasonable to describe the MT model (3) with the following linear state space model in a certain operating range. For different MTs, the range can be obtained by monitoring actual operation.

$$\begin{cases} \hat{x}_{es}(k+1) = A\hat{x}_{es}(k) + Bu(k) + \omega(k) \\ \hat{y}_e(k) = C\hat{x}_{es}(k) + Du(k) + \upsilon(k) \end{cases} \tag{4}$$

where A, B, C, and D represent the system model matrices, $\hat{x}_{es}(k)$, $u(k)$ and $\hat{y}_e(k)$ represent state, input and output vector at time k, $\omega(k)$ and $\upsilon(k)$ are vectors of Gaussian distributed, zero mean, white noise sequences, $k = 1, 2, ..., N_e$, N_e is the length of the electro-mechanical system data record.

In this paper, the subspace identification method is employed to model the MTs, which could estimate model outputs and state variables simultaneously with the state space form. It is capable of handling the measurement noise and extracting the model from real operation data. Further, optimisation is not required in the subspace modelling [36], unlike some other black-box modelling approaches. And this will significantly enhance its applicability to real applications, especially when it is used for online applications. By choosing different orders, the accuracy and the complexity can be compromised according to different model requirements.

Both normal and low pressure natural gas source can be utilised to feed the MT [37]. The fuel intake pressure level is maintained at a certain level by controlling the compressor and valve positions. When the fuel pressure is too low, the adjustment ability may reach its upper bound, which will further cause MT output saturation. Mechanism analysis shows that key states of the MT, such as the engine speed, is closely related to the MT outputs, which indicates it is possible to estimate the MT internal state with its outputs. With the subspace identification method, dominant states of the MT can be estimated. The obtained model is thus able to predict the output saturation, and analyse its dynamic impacts of MTs on distribution networks. Although the internal states of MTs may not be available, both system states and outputs of the obtained model can still be corrected directly or indirectly, by using the observed inputs and outputs online.

Based on the characteristics of the practical operation data, a piecewise method can be utilised to identify the behaviours of the MT in various operating range. The saturation range can be incorporated as a nonlinear extension of the piecewise linear models of the MT.

2.3. Three-stage identification method

As shown in Fig. 2, a three-stage identification method, which takes into account both linear and saturation operating range, is developed in this paper so as to model the MT electro-mechanical subsystem.

Considering the disturbance caused by the external environment, the subspace state space system identification (N4SID) [38] is used to obtain the model in (4). The saturation of system state variables is identified and estimated based on the operation data. A detailed description of the modelling process is described as follows.

Stage I: Pre-processing.

Step 1: Fundamental mechanism analysis. The time scale and linearity characteristics of the MT is analysed in order to estimate the system order in (4).

Step 2: Input and output signals selection. To maximize the efficiency and reduce operational costs, MTs are often used for cogeneration, creating both electricity and heat [39]. The power output can be adjusted by changing load signals of the MT. Since the impact of electric output is more critical for the distribution network analysis, the load signal and the power output are defined as input and output signals.

Step 3: Data recording. If the field condition allows physical experiments, then design various scenarios for system identification. Otherwise, the system operation data will be obtained from online monitoring. For utility owned MTs, detail informations are acquired by specially designed experiments. For customer owned MTs, historical and real-time operating data can be obtained by monitoring the interface between customers and utilities. To ensure the MT operation security, the engine speed is also monitored.

Step 4: Data extraction. The obtained data are divided into several datasets, and further classified into modelling and validation sets.

Stage II: Model identification.

Step 5: As mentioned in Step 1, the load signals and MT power outputs data are recorded as input $U_0, U_1, ..., U_{2i-1}$ and output $Y_0, Y_1, ..., Y_{2i-1}$ data vectors.

Step 6: System order n_x specification. In the N4SID, the number of relative large singular values is usually used as an estimation of the system order. However, there is no distinct boundary between large and small values in some scenarios. Thus, n_x is firstly analysed based on the priori knowledge. If it can be specified, n_x is utilized in the N4SID to model the electro-mechanical subsystem. Otherwise, Akaike Information Criterion (AIC) defined by (5) will be used to estimate the system order [27].

$$AIC = ln(J(1 + 2\frac{d}{N})) \tag{5}$$

where d is the total number of estimated parameters, N is the length of the data record. J is the estimated residual of the model, calculated by $J = \sum_{t=t_0}^{t=t_1}[y(t) - \widehat{y}(t)]^2$, t_0 and t_1 represent the start and end of the sampling time.

Step 7: Estimate the system matrix A, B, C, D by solving a set of overdetermined equations.

Stage III: Saturation incorporation.

Step 8: Saturation capture. The MT engine is coupled with the compressor by the shaft. When the fuel intake level is low, the engine speed will be increased in order to absorb more fuel. It may reach its upper bound which will also constrain the MT output power. Therefore, the saturation region of the speed is monitored to indicate the MT output upper bound and adjust the model developed in Stage II.

Step 9: Upper bound incorporation. The engine speed upper bound ω^{upper} is estimated by comparing the estimated states with the normalized observed states $\widehat{X}_{i+1}$. In this paper, two main external factors (natural gas network and temperature) that affect the MT operation are incorporated in the modelling process. Considering the slow dynamics of the two factors, a upper bound obtained from practical operation data will be used to adapt to the external environment variation. Then the model output P_{out} can be estimated as follows:

$$P_{out} = \begin{cases} Y_i, \widehat{X}_{i+1} \leq \omega^{upper} \\ P_{out}^{upper}, \widehat{X}_{i+1} \geq \omega^{upper} \end{cases} \tag{6}$$

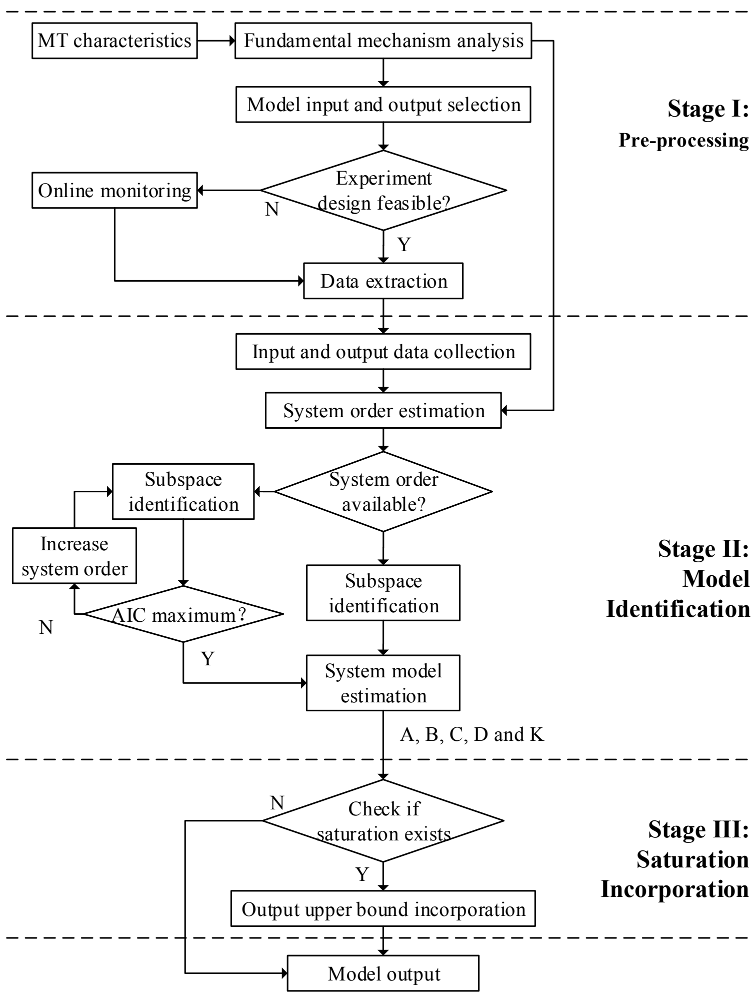


Figure 2: Flowchart of the electro-mechanical system identification process.

3. Dynamic analysis of distribution networks based on the identified MT model

In a distribution network, multiple MTs may exist with very limited data available to utilities. To address this issue, an online data acquisition and model identification method is presented to simulate dynamic behaviours of various MTs in a distribution network. As shown in Fig. 3, the proposed method can then be summarized as follows.

Step 1: Input data. Collect distribution network and MT historic operation data including MT load signals, power outputs, and operating states.

Step 2: Identify the MT model. Based on MT operating modes, a mathematical MT model can be obtained using the three-stage identification method proposed above to build the electro-mechanical model for MTs.

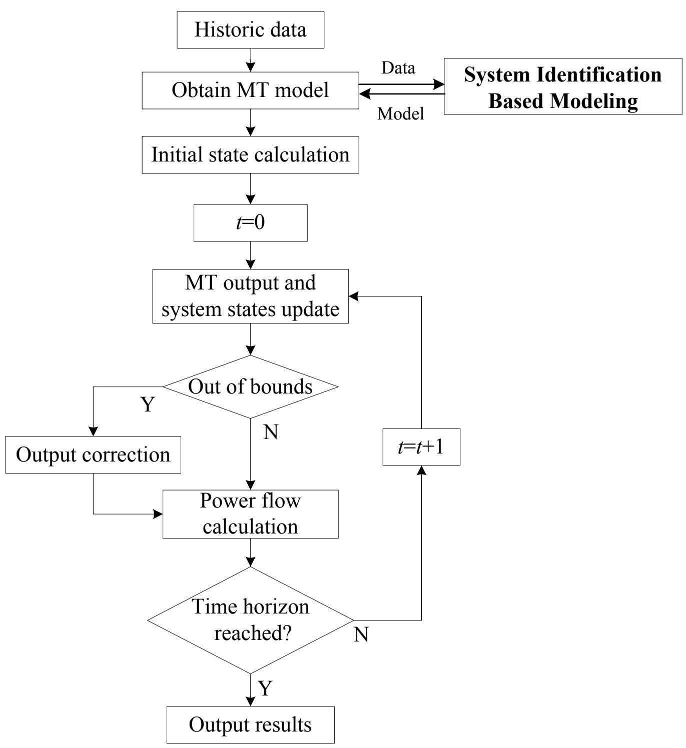


Figure 3: Flowchart of MT modeling and fast simulation process

Step 3: Initialize MT state variables and simulation parameters.

1) Initialize state variables of the obtained MT model and let $t = 0$.

2) Set the simulation step t_{sim} and the scheduling period t_{sch}.

Step 4: Generate MT power output series.

1) Select an array of MT set-points.

2) Generate MT output response: Generate the power output and system state array using the model obtained in Step 2 with step size t_{sim}.

Step 5: Update system states and MT outputs. If either system states or MT outputs exceed the bounds, the model will be corrected using (6). Otherwise, continue.

Step 6: Calculate the power flow.

1) Set MTs which are integrated into the distribution network to active-reactive power control mode[1], and the bus embedded with MTs as a load bus in the electric power flow calculation.

2) Call the power flow time series model to simulate the distribution system.

Step 7: Stop criterion. If a pre-determined time horizon is reached, output results; otherwise, let $t = t + t_{sch}$, and go to Step 4.

4. Experimental studies

4.1. MT model test

Fig. 4 shows a Capstone C30 MT at the Smart Grid Lab of Tianjin University. The MT obtains fuel from the local gas network, and supplies both power and heat to the lab. It is observed that the MT output cannot follow the load signal, when the gas pressure level is low. In this section, we apply the proposed identification method to model the MT under both the normal operating state and the saturation state. The MT was operated in the grid-connected mode, in order to use the obtained model in analysing the impacts of MTs on distribution networks. The rated electric output and shaft speed are 30 kW and

[1] In practice, the MT can also be used in other control modes, which can be solved by changing bus types in the power flow calculation of distribution networks

Figure 4: Capstone C30 MT experimental platform.

96000 RPM. Other parameters supplied by the manufacture can be found in [37]. The experimental data was collected by remote monitoring software of the MT. The sampling rate was set at 4 Hz. To ensure the MT efficiency, the load signal ranging from 5 kW to its rated power was selected to cover the normal operating range. The reactive power output of the MT was set to zero in the whole process. For identification and validation purposes, three groups of field measurement data were collected over various periods of time.

4.1.1. Model identification

In the proposed methodology, the system order, which plays a key role in the modelling process, can be determined by the mechanism analysis or the AIC. Thus, both the dominant order model and the AIC maximum model were tested. In previous studies, MTs are shown to have 2^{nd} order dynamic characteristics [35, 40], which implies that two state variables dominate the MT dynamics. The system order is thus set to be 2 in the dominant model. It should be pointed out that dominant orders of MTs might be different due to the existence of complex system behaviours and control systems. For the AIC maximum model, the overall trend of the AIC index decreases as the system order goes up, as shown in Fig. 5. Because the AIC has almost no change when the system order

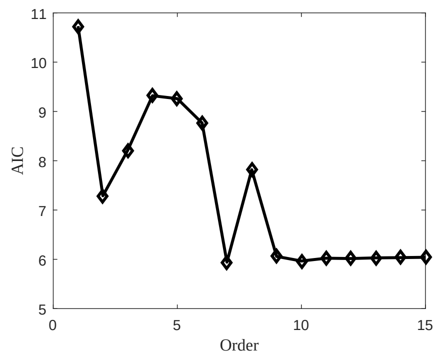


Figure 5: The AIC of different system order.

is above 7, the order of the AIC maximum model is chosen to be 7 in the following studies. For real applications, the system order of the MT model can be estimated based on the priori knowledge and accuracy requirements.

Following the algorithm shown in Fig. 2, we firstly analyse the first group of data, which is used to identify the model in the normal operating range. As depicted in Fig. 6, the AIC maximum model (the dashed green line) which has higher order captures the short-term fluctuation better than what the dominant order model does (the dotted red line). However, higher order indicates larger calculation burden. In order to use the model for the long-term simulation of large-scale systems, the dominant order model, which has lower order, is chosen to simulate the MTs accessed to distribution networks. It should be noted that a distinct mismatch (as depicted in the dashed brown line) happens when the power output is close to 25 kW, although the MT can still follow the load signal after a short term adjustment. This phenomenon implies that the MT output is driven near the saturation region in the current situations. The border line between the unsaturation state and the saturation region could be different, when external conditions change. With the system identification method, the border line could be distinguished and corrected based on the real time data, which makes the proposed method an effective tool in predicting the behaviours of the MT, especially for the long-term simulation. Moreover,

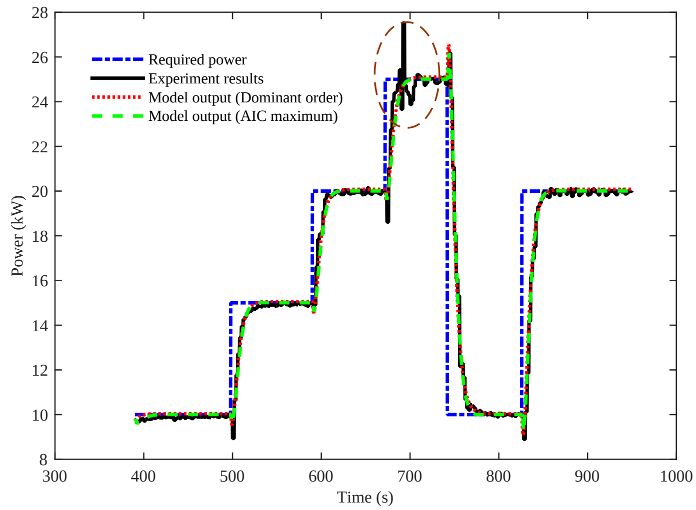
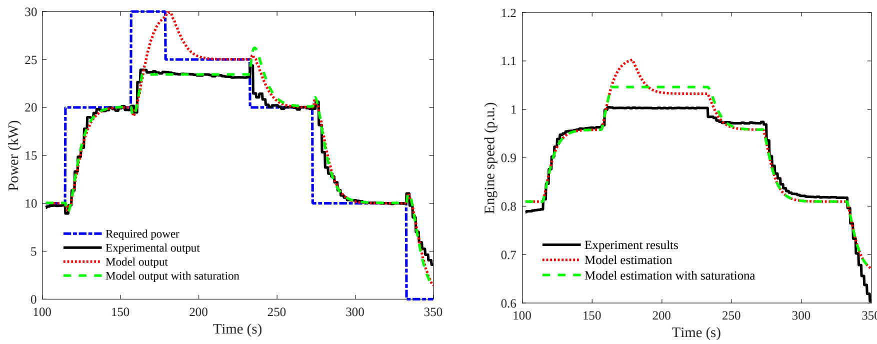


Figure 6: Identification results of the electromechanical system in normal states.

although measurement noise exists in the studied data recorded from physical experiments, the behaviours of the MT output can still be approximated well. It indicates that the proposed method has the ability to handle the measurement noise, which is critical for practical applications.

In order to cover the saturation region, we also examine the MT output under the conditions of low gas pressure. The studied MT is accessed to a natural gas network, which also supplies gas to a restaurant. The pressure level of the gas level goes down during lunch and dinner periods, and the MT outputs may not be able to follow the load signal in these periods, as shown in Fig. 7. According to the analysis in Section 2, the MT output saturation can be reflected by generator speed constraints. To predict the saturation occurrence, state variables obtained by the N4SID were utilized to estimate the MT engine speed. As shown in Fig. 7a and Fig. 7b, an accurate approximation can be observed for the MT speed and power output within the range between 5 kW and 20 kW. The MT output saturation in Fig. 7a could be captured under the predefined speed constraint, in which the speed constraints are not the same under different external environment. Since natural gas networks and



(a) Power output

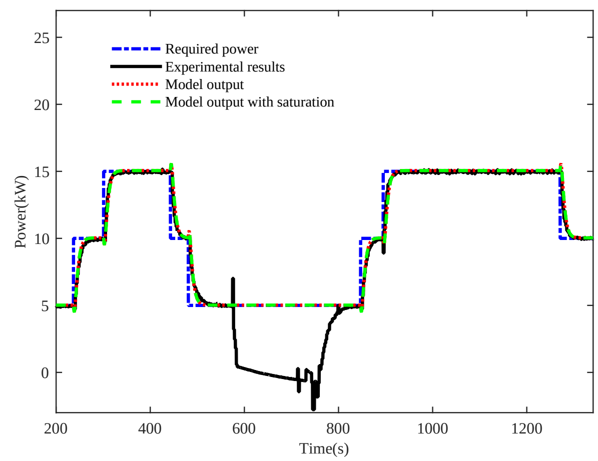
(b) Engine speed

Figure 7: Test results of the MT in the saturation state.

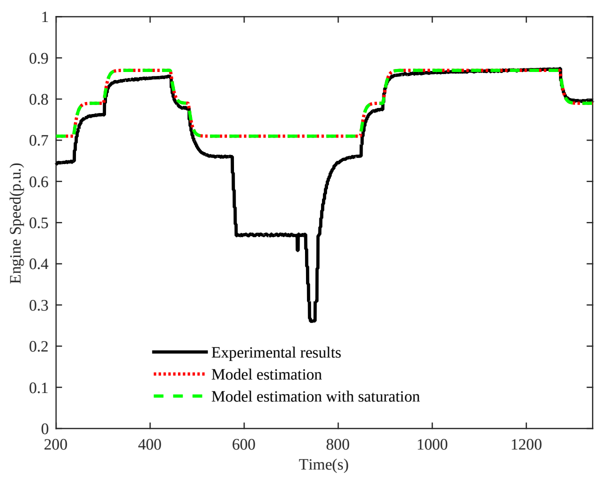
temperatures change much slower than the electric dynamics, it is reasonable to estimate the speed constraints by observing the system operation in previous data collection cycles. Therefore, the proposed modelling method could assist in predicting the MT output saturation, and provide important guidance to further quantify the impacts of low gas pressure on MT outputs and distribution networks.

4.1.2. Model validation

In order to demonstrate the generalization ability of the proposed modelling method, more experimental data and model outputs are to be presented. To be different from the previous cases, the MT output were changed to lower levels in this case, with a minimum output of 5 kW. As shown in Fig. 8, the identified model can produce a good approximation of the experimental results in most scenarios, when the MT output is above 5 kW. Similar results can be found in Fig. 7. Thus, we can conclude that the suitable application range of the developed model for the studied MT would be between 5 kW and 25 kW. It can also be seen from Fig. 8b that the proposed model approximates the engine speed well when the power output is above 10 kW. As the power output goes down, the speed deviates from the experimental results evidently, especially when the power output is below 5 kW.



(a) Power output



(b) Engine speed

Figure 8: Generalization ability tests of the electromechanical model.

It should be noted that large deviations can be observed after 574 s, due to an accidental shutdown of the MT caused by the fault of the gas pipeline, and the MT output recovers after the fault is cleared. However, these deviations cannot affect the effectiveness of the proposed modelling method, because the obtained model is used for long-term analysis of the MT, not for short-term fault diagnosis. In addition, the MT output during the fault period is below 5 kW, which is the output of the effective range of the obtained model. Combining with the previous two cases, we can conclude that the proposed modelling method is robust in both the normal operating state and the saturation state.

4.2. Simulation of distribution networks with multiple MTs

One of the important applications of the proposed modelling method is to assist utilities and customers in analysing distribution networks with multiple MTs. In this section, we apply the proposed modelling and simulation method

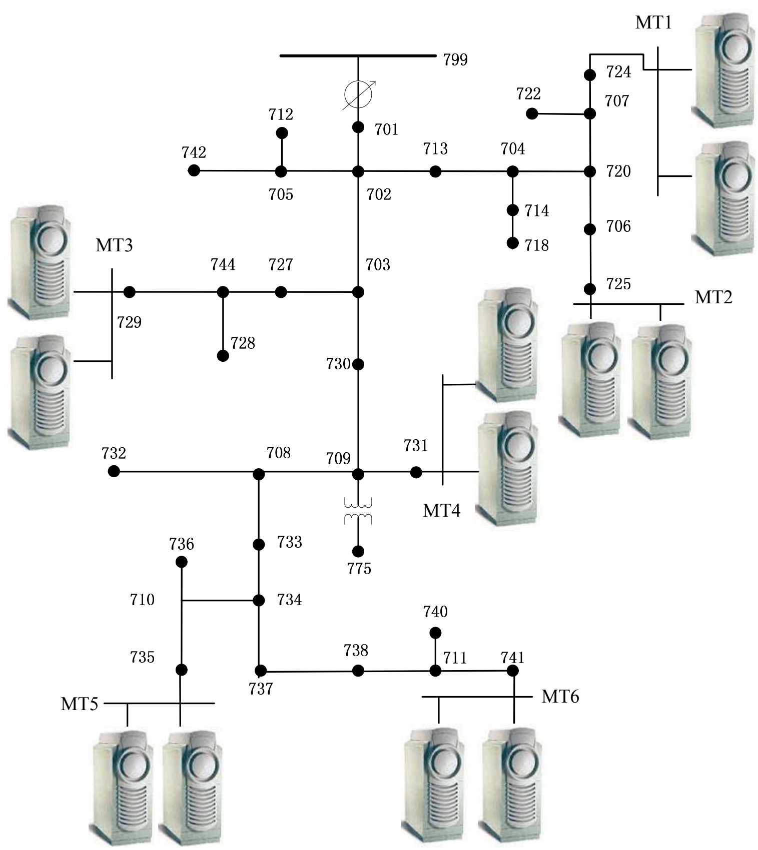


Figure 9: The IEEE 37-Node test feeder augmented with six groups of MTs.

to simulate the behaviours of the IEEE 37-Node system. Six groups of parallel Capstone C30 MTs are accessed to buses 724, 725, 729, 731, 735, and 741 of the system, as shown in Fig. 9. Active load (from buses 724, 728, 709, 736, and 740) variations are considered in the tests. To be simplified, all the five loads are assumed to follow the same change pattern, as shown in Fig. 10. During the simulation, MTs were operated under the active-reactive power control mode and scheduled to balance the load variations. An average load sharing scheduling algorithm was employed to smooth tie-line power fluctuations. For simplicity, the scheduling objective was to keep the power constant at the point of common coupling of the distribution network to the main grid (bus 701). All MTs were scheduled with the same load signals. Based on the identified results, the states of MTs were marked as either normal or saturation state.

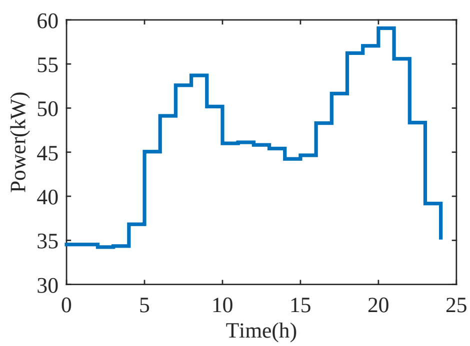


Figure 10: Electric load demand variation curve in the five buses.

Because the dominant order and the AIC maximum models are both involved in the modelling process, the two models are investigated and compared with each other. Considering that local distribution networks are usually coordinated as a microgrid in the smart grid environment, the power flow of the tie-line is thus a key index in the distribution network studies. As one of the most successful commercialised DERs, MTs are usually used in smoothing the power exchange within the tie-line. With the proposed simulation method, dynamic variation of the tie-line power could be demonstrated as shown in Fig. 11.

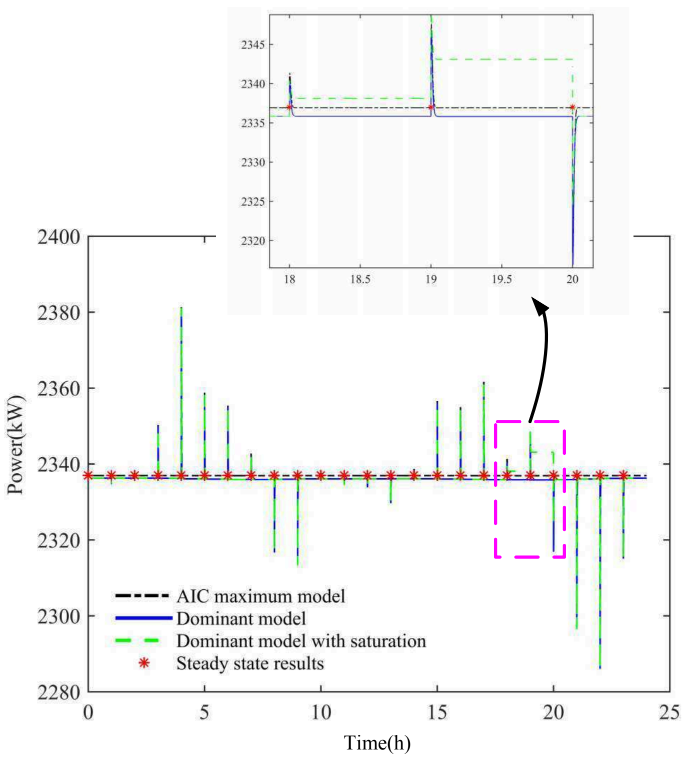


Figure 11: Comparison of the tie-line power fluctuation.

It is clear that the fluctuation dynamics can be captured by the proposed model accurately, which is crucial for evaluating dynamic impacts of the MTs on the distribution network. The results also show that the electric characteristics obtained by the two models are quite close. Compared with steady state simulation results, it can be found that both the two models can capture the dynamic fluctuation. Since higher order model provides better approximation results, there exist some mismatches between simulation results of the two models, as shown in Fig. 11. Therefore, it is rational to integrate the proposed models in the long-term analysis of a distribution network with multiple MTs, in order to balance the requirements of the model accuracy and computational costs.

As mentioned above, the outputs of various MTs could saturate simultaneously when the pressure of the accessed gas network is low. To take this into account, a simplified test was carried out by assuming that the saturation occurs at buses 724, 729, and 735. The ambient conditions of the associated MT inlets were assumed to be the same as those of the identified MT model in Section 4.1. With the obtained model, the system is simulated for a period of 24 hours. As illustrated in Fig. 12, the MT model output without saturation (see the dotted blue line) follows the desired MT model output (see the red line) well. Nevertheless, the mismatch that exists between the normal output and the saturation output significantly affects the scheduling results of the distribution network. It can be seen from Fig. 12 that the MT output saturation can be well captured by the model at 19 h, as depicted in the the dotted green cycle. The relative tie-line power with MT output power saturation is shown in Fig. 11. The mismatch between saturation and unsaturation cases confirms that it is necessary to model the MT saturations and estimate the impacts of the natural gas system, as discussed earlier in this paper. Also, it can be seen that the proposed simulation method is able to analyse the negative effects of the natural gas network on the distribution systems, including the network, loads, and other DERs. If used online, the proposed model can also help the

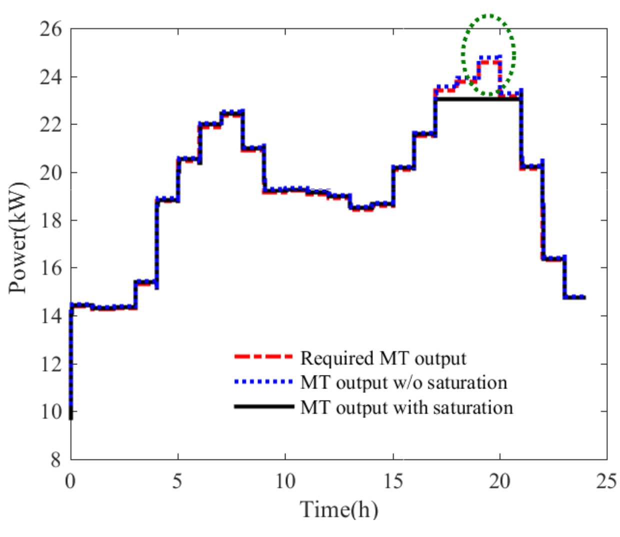


Figure 12: Comparison of MT power output with and without saturation

operators to predict the saturation caused by the low gas pressure, and to avoid the scheduling failure of MTs.

It is worth mentioning that although the same type of MTs were studied and scheduled with the same signals in this paper, the proposed method is still effective for MTs with various brands and capacity, as long as the MT information and scheduling signals are obtainable.

5. Conclusion

This paper investigates the long term impact of multiple MTs on the distribution network. A three-stage modelling method is developed to describe the MT electric output characteristics. The feasibility of using the state space model to predict the MT electric output is investigated based on the time-scale characteristics as well as the linear characteristics of the MT within a certain operating range. The resultant model is then integrated into a fast simulation scheme to evaluate the performance of the distribution network with multiple MTs. Experimental and numerical examples were conducted to demonstrate the effectiveness and accuracy of the obtained models under different operation scenarios. The experimental results conform that the new lower order MT model can accurately predict the MT power output, and well capture its saturation caused by low gas pressure. This allows the simulation of dynamic behaviours of MT electric output with a lower level of model complexity, which is difficult to achieve when using traditional MT models. With the obtained model, the influence of multiple MTs on the distribution network was analysed numerically with promising results.

Although this paper focuses on the incorporation of MTs into dynamic analysis of distribution networks, the developed method can also be utilised for distribution networks with other energy conversion units, such as air-conditioners and heat pumps, where simplified system models and parameters need to be identified. By embedding the proposed modelling method into simulation packages, it is possible for planners and operators to analyse dynamic impacts of energy conversion units on distribution networks. Since the obtained model can be built for most of the operating ranges, it can also be used for control system design of MTs in coupled energy systems.

Acknowledgement

The authors would like to thank Dr Joseph Devlin for his contribution to our manuscripts. This work is supported in part by the UK-China NSFC/EPSRC Project (Grant No. EP/L001063/1 and 51361130153), the China NSFC Project (Grant No. 5160717 and 61533010) and the National High-tech R&D Program of China (Grant No. 2015AA050403). The authors are grateful to the helpful comments from the editor and reviewers which have significantly improved the quality of the paper.

References

[1] A. S. Kocaman, W. T. Huh, V. Modi, Initial layout of power distribution systems for rural electrification: A heuristic algorithm for multilevel network design, Applied Energy 96 (2012) 302–315.

[2] D. Pudjianto, P. Djapic, M. Aunedi, C. K. Gan, G. Strbac, S. Huang, D. Infield, Smart control for minimizing distribution network reinforcement cost due to electrification, Energy Policy 52 (2013) 76–84.

[3] S. Sanaye, M. R. Ardali, Estimating the power and number of microturbines in small-scale combined heat and power systems, Applied Energy 86 (6) (2009) 895–903.

[4] R. Viral, D. Khatod, Optimal planning of distributed generation systems in distribution system: A review, Renewable and Sustainable Energy Reviews 16 (7) (2012) 5146–5165.

[5] J. Devlin, K. Li, P. Higgins, A. Foley, The importance of gas infrastructure in power systems with high wind power penetrations, Applied Energy 167 (2016) 294–304.

[6] M. Chaudry, N. Jenkins, M. Qadrdan, J. Wu, Combined gas and electricity network expansion planning, Applied Energy 113 (2014) 1171–1187.

[7] T. Olofsson, T. Mahlia, Modeling and simulation of the energy use in an occupied residential building in cold climate, Applied Energy 91 (1) (2012) 432–438.

[8] V. Harish, A. Kumar, A review on modeling and simulation of building energy systems, Renewable and Sustainable Energy Reviews 56 (2016) 1272–1292.

[9] F. Jurado, Non-linear modeling of micro-turbines using NARX structures on the distribution feeder, Energy conversion and management 46 (3) (2005) 385–401.

[10] X. Liu, J. Wu, N. Jenkins, A. Bagdanavicius, Combined analysis of electricity and heat networks, Applied Energy 162 (2016) 1238–1250.

[11] M. Rees, J. Wu, N. Jenkins, M. Abeysekera, Carbon constrained design of energy infrastructure for new build schemes, Applied Energy 113 (2014) 1220–1234.

[12] B. Morvaj, R. Evins, J. Carmeliet, Optimization framework for distributed energy systems with integrated electrical grid constraints, Applied Energy 171 (2016) 296–313.

[13] R. C. Dugan, Reference guide: the open distribution system simulator (OpenDSS), Electric Power Research Institute, Inc.

[14] X. Jin, Y. Mu, H. Jia, J. Wu, X. Xu, X. Yu, Optimal day-ahead scheduling of integrated urban energy systems, Applied Energy 180 (2016) 1–13.

[15] D. Chassin, K. Schneider, C. Gerkensmeyer, GridLAB-D: An open-source power systems modeling and simulation environment, in: 2008 IEEE/PES Transmission and Distribution Conference and Exposition, 2008.

[16] K. P. Schneider, J. C. Fuller, D. P. Chassin, Multi-state load models for distribution system analysis, Power Systems, IEEE Transactions on 26 (4) (2011) 2425–2433.

[17] C. Liu, M. Shahidehpour, J. Wang, Coordinated scheduling of electricity and natural gas infrastructures with a transient model for natural gas flow, Chaos: An Interdisciplinary Journal of Nonlinear Science 21 (2) (2011) 025102.

[18] X. Xu, H. Jia, H.-D. Chiang, D. Yu, D. Wang, Dynamic modeling and interaction of hybrid natural gas and electricity supply system in microgrid, Power Systems, IEEE Transactions on 30 (3) (2015) 1212–1221.

[19] M. Qadrdan, M. Abeysekera, M. Chaudry, J. Wu, N. Jenkins, Role of power-to-gas in an integrated gas and electricity system in great britain, international journal of hydrogen energy 40 (17) (2015) 5763–5775.

[20] M. Qadrdan, M. Chaudry, N. Jenkins, P. Baruah, N. Eyre, Impact of transition to a low carbon power system on the gb gas network, Applied Energy 151 (2015) 1–12.

[21] S. Massucco, A. Pitto, F. Silvestro, A gas turbine model for studies on distributed generation penetration into distribution networks, Power Systems, IEEE Transactions on 26 (3) (2011) 992–999.

[22] W. I. Rowen, Simplified mathematical representations of heavy-duty gas turbines, Journal of Engineering for Gas Turbines and Power 105 (4) (1983) 865–869.

[23] S. Grillo, S. Massucco, A. Morini, A. Pitto, F. Silvestro, Microturbine control modeling to investigate the effects of distributed generation in electric energy networks, Systems Journal, IEEE 4 (3) (2010) 303–312.

[24] A. Saha, S. Chowdhury, S. Chowdhury, P. Crossley, Modeling and performance analysis of a microturbine as a distributed energy resource, Energy Conversion, IEEE Transactions on 24 (2) (2009) 529–538.

[25] M. Kalantar, et al., Dynamic behavior of a stand-alone hybrid power generation system of wind turbine, microturbine, solar array and battery storage, Applied energy 87 (10) (2010) 3051–3064.

[26] H. Nern, H. Kreshman, F. Fischer, H. Eldin, Modelling of the long term dynamic performance of a gas turbo generator set, in: Control Applications, 1994., Proceedings of the Third IEEE Conference on, IEEE, 1994, pp. 491–496.

[27] L. Ljung, System identification, Springer, 1998.

[28] M. Basso, L. Giarre, S. Groppi, G. Zappa, NARX models of an industrial power plant gas turbine, Control Systems Technology, IEEE Transactions on 13 (4) (2005) 599–604.

[29] A. E. Ruano, P. J. Fleming, C. Teixeira, K. RodrıGuez-Vázquez, C. M. Fonseca, Nonlinear identification of aircraft gas-turbine dynamics, Neurocomputing 55 (3) (2003) 551–579.

[30] H. Nikpey, M. Assadi, P. Breuhaus, Development of an optimized artificial neural network model for combined heat and power micro gas turbines, Applied Energy 108 (2013) 137–148.

[31] R. Bettocchi, M. Pinelli, P. Spina, M. Venturini, Artificial intelligence for the diagnostics of gas turbines Part I: neural network approach, Journal of engineering for gas turbines and power 129 (3) (2007) 711–719.

[32] M. Fast, M. Assadi, S. De, Development and multi-utility of an ANN model for an industrial gas turbine, Applied Energy 86 (1) (2009) 9–17.

[33] E. Mohammadi, M. Montazeri-Gh, A new approach to the gray-box identification of wiener models with the application of gas turbine engine modeling, Journal of Engineering for Gas Turbines and Power 137 (7) (2015) 071202.

[34] H. Nikkhajoei, M. R. Iravani, A matrix converter based micro-turbine distributed generation system, Power Delivery, IEEE Transactions on 20 (3) (2005) 2182–2192.

[35] Z. Li, D.-H. Wang, Y.-L. Xue, D.-H. Li, Research on ways of modeling of micro gas turbines (ii): Reduction and analysis, Power Engineering 2 (2005) 002.

[36] T. Katayama, Subspace methods for system identification, Springer Science & Business Media, 2006.

[37] Capstone Turbine Corporation, http://www.capstoneturbine.com/products/c30, C30 MicroTurbine Natural Gas [Online].

[38] B. Peeters, System identification and damage detection in civil engeneering, Ph.D. thesis (2000).

[39] L. Li, H. Mu, N. Li, M. Li, Analysis of the integrated performance and redundant energy of CCHP systems under different operation strategies, Energy and Buildings 99 (2015) 231–242.

[40] D. Yue, K. Li, A modeling approach of DC link of micro-gas turbine generation system, POWER SYSTEM TECHNOLOGY-BEIJING- 32 (3) (2008) 13.