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Distributed and decentralized state estimation in gas networks as distributed parameter systems

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ABSTRACT

In this paper, a framework for distributed and decentralized state estimation in high-pressure and long-distance gas transmission networks (GTNs) is proposed. The non-isothermal model of the plant including mass, momentum and energy balance equations are used to simulate the dynamic behavior. Due to several disadvantages of implementing a centralized Kalman filter for large-scale systems, the continuous/discrete form of extended Kalman filter for distributed and decentralized estimation (DDE) has been extended for these systems. Accordingly, the global model is decomposed into several subsystems, called local models. Some heuristic rules are suggested for system decomposition in gas pipeline networks. In the construction of local models, due to the existence of common states and interconnections among the subsystems, the assimilation and prediction steps of the Kalman filter are modified to take the overlapping and external states into account. However, dynamic Riccati equation for each subsystem is constructed based on the local model, which introduces a maximum error of 5% in the estimated standard deviation of the states in the benchmarks studied in this paper. The performance of the proposed methodology has been shown based on the comparison of its accuracy and computational demands against their counterparts in centralized Kalman filter for two viable benchmarks. In a real life network, it is shown that while the accuracy is not significantly decreased, the real-time factor of the state estimation is increased by a factor of 10.

1. Introduction

Natural Gas Transmission Companies (NGTCs) use high pressure and long distance pipelines to transmit natural gas from production sites to the customers. As there are different types of natural gas consumers, where some customers use constant amounts of gas and others follow a time-varying consumption pattern, safe operation of the transmission system is the responsibility of the NGTC. The successful fulfilment of these tasks requires accurate information about of the current status of the network, which is a challenging task due to the lack of reliable information about many process variables. In a GTN, measuring devices are installed at specific points for the measurement of pressure, temperature and flow, and many variables remain unmeasured considering economic and technical limitations. These limitations encourage us to employ state estimators to reconstruct the unmeasured variables or smooth the measured variables due to the presence of measurements noise. Variable customer demand is a characteristic that makes dynamic real-time optimization an appropriate alternative for GTNs, in which a dynamic data reconciliation is an essential module [1]. Total line-pack of the network, which is the quantity of gas contained in pipelines [2,3], helps the gas dispatchers in the reliable operation of the network under the time-varying customer demands or abrupt load changes. There are many methods for leak detection in a gas network [4–6], among which model based estimation techniques enable us for on-line monitoring to detect leaks during gas network operation. So, an observer is required to reconstruct the states, and the reconstructed states are then compared with the available measured variables to generate the residuals. Accordingly, there are many problems in the field of gas transmission which require efficient state estimation methods such as dynamic data reconciliation, determining the line-pack of the pipelines, leak detection, demand estimation, optimal sensor placement [7] and regulatory control.

Bagajewicz and Cabrera [8] proposed an iterative steady-state data reconciliation framework for GTNs, based on mass balance equations and an approximate form of mechanical energy balances. Reddy et al. [9] used Laplace transform to develop an isothermal transfer function model of GTNs, and proposed a data reconciliation framework based on this model. They also

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Nomenclature

A_c	cross section area of the pipe [m^2]
C_p	heat capacity at constant pressure [J/kg K]
c_v	valve conductance at fully open state [GPM]
D	inner diameter of the pipe [m]
f_r	friction factor [-]
g	standard gravity [m/s^2]
k	index of the sampling time
K	compressor adiabatic power [kW/MMSCMD]
l	spatial coordinate [m]
$L_i(x)$	Lagrange polynomial
m	mass flow rate [kg/s]
M	number of measurements in global system
$\underline{M}$	integration time intervals for the dynamic block Jacobi-like iteration scheme
N	number of states in global system
N_i	number of states in subsystem i
N_{SS}	number of processing units or local systems
N_{Oi}^{+}	set of O-neighborhood nodes of the node i and the node i itself
$N_{E,i}$	E-neighbor of subsystem i
$N_{O,i}$	O-neighbor of subsystem i
N_c	number of internal collocation points
p	pressure [Pa]
P	state covariance matrix
P_i	state covariance matrix for subsystem i
R	universal gas constant [J/kg K]
t	time [s]
T	temperature [K]
T_{ij}	inter-nodal transformation matrix
$T_i \in \mathbb{R}^{N_i \times N}$	nodal transformation matrix
$\overline{T}_i$	integration time for the dynamic block Jacobi-like iteration scheme
T_S	sample time
T_{CC}	time interval in which dynamic block Jacobi-like iteration scheme is convergent
$u \in \mathbb{R}^{M \times 1}$	known input
υ_{avg}	average specific volume
$v(k)$	measurement noise $\mathcal{N}(0, R)$
υ_s	inlet specific volume [m^3/kg]
V_w	isentropic speed of sound wave [m/s]
$w(t)$	process noise $\mathcal{N}(0, Q)$
W	valve mass flow rate [kg/s]
$X \in \mathbb{R}^{N \times 1}$	state vector of the global system
$X_{si,i}$	states of interest of subsystem i
$X_{os,i}$	overlapping states of subsystem i
$X_{es,i}$	external states of subsystem i
$X_{r,i}$	relevant states of subsystem i
$X_i \in \mathbb{R}^{N_i \times 1}$	local state vector
Y	measurement vector in global system
Z	compressibility factor [-]
Ω	rate of heat flow into the pipe per unit length of pipe [J/m s]
τ_w	shear stress at the wall
ρ	density of the gas [kg/m^3]
η_{id}	thermodynamic efficiency of compressors
$\gamma = C_p/C_v$	ratio of constant pressure and constant volume heat capacities
θ	pipe inclination angle with respect to horizon [radian]
v	velocity along the pipe axis [m/s]
α, β	Jacobi polynomial parameters
$\Gamma\langle\rangle$	an operator which eliminates rows with all zero elements of its input matrix
$\frac{d\upsilon}{dT}$	derivative of specific volume with respect to temperature
$\kappa(\lambda)$	flow characteristic of the valve
λ	valve opening percentage [$\lambda = 100\%$ for max flow]

Subscripts

S	discharge side of a compressor or valve
d	suction side of a compressor or valve

demonstrated the application of measurement redundancy in the estimation of unknown demands.

Here, the development of a state estimator for natural gas transmission systems is based on the extension of Kalman filter for nonlinear systems. Centralized implementation of the Kalman filter has severe limitations such as tuning, scalability and lack of robustness in case of sensor failures. Large dimension of the state vector in a GTN also creates additional difficulties in estimator design and implementation due to the initialization and tuning of estimator parameters in the design stage and high computational demand in its implementation. These problems limit the applicability of centralized Kalman filter for systems with a large number of states. Distributed and decentralized architectures are alternative approaches [10,11] which result in more flexibility in design, implementation and extension.

The major research activities on distributed Kalman filters are around low dimension systems monitored by multiple sensors. Berg and Durrant-Whyte [10], based on construction of local models by ignoring unimportant dynamic interactions, discussed model distribution in decentralized multi-sensor data fusion. Mutambara [11] developed a fully distributed and decentralized estimation and control structure to achieve the same performance of a centralized algorithm under certain conditions for linear and non-linear discrete plants. He also discussed various aspects of the algorithm proposed by Berg and Durrant-Whyte [10]. Vadigepalli and Doyle III [12] applied the framework proposed by Mutambara [11] in chemical engineering problems for linear discrete-time systems, and they studied an industrial reaction–separation system and a pulp mill plant as their benchmarks. They also proposed some heuristic guidelines for decomposing the global system to compromise the computational burden and the required communication in the distributed and decentralized estimation and control network. Mercangöz and Doyle III [13] also used Mutambara‘’s estimation algorithm for the linear time-invariant discrete-time systems. However, they replaced its state-feedback control structure with a distributed model predictive control algorithm. They showed that the communication among relevant nodes improves the performance compared to completely decentralized controllers. Lendek et al. [14] studied the distribution of Kalman filter for cascaded systems. They decomposed a linear process model into cascaded simpler subsystems and designed a suboptimal Kalman filter for each subsystem. Khan and Moura [15] presented a distributed Kalman filter with reduced-order models for sparsely connected large-scale systems, where important coupling among the system variables is preserved. Abdel-Jabbar et al. [16] proposed decentralized state observer for linear and non-linear continuous systems where the model used in the simulation contains the interaction terms, while the implemented model based controller is using the states obtained through fully decentralized