Eigenvector Analysis for the Ranking of Control Loop Importance

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Abstract

A methodology for optimizing the prioritization of base layer control loop maintenance by identifying control loops that have the greatest impact on overall plant-wide profitability and/or safety is presented. The methodology is based on a modified form of the LoopRank algorithm originally proposed by Farenzena and Trierweiler (2009) and takes into account connectivity metric, performance measures and economical attributes. Various methods of obtaining a connectivity metric are investigated, with the modified transfer entropy suggested by Shu and Zhao (2013) providing the best results. The well-known Tennessee Eastman Plant problem is used to demonstrate the effectiveness of the methodology.

<<Use of Oxford comma?>>

Colour legend:

TODO

General unreferenced statement to verify

Redundant or just a bit meh.. – still figuring out the most compact way to say things

Question

**Keywords**: prioritization, maintenance, fault detection, connectivity, causal mapping

* 1. Introduction

The large number of loops present on a typical industrial chemical processing plant necessitates the prioritization of control loop maintenance and optimization. Base layer control engineers and technicians often follow a “fighting today’s fire” approach as no definite measure is available to identify the faulty control loops that have the highest effect on overall performance. In the proposed method connectivity, control loop performance measures and economical attributes are combined to identify control loops with the greatest influence on profitability and/or stability. This will allow more efficient use of control engineer and instrumentation specialist man hours, in turn leading to safer and more economical plant operation.

A plant may be modelled as a directed graph where the nodes represent the variables and the edge connectivity is inferred from the physical and logical structure of the plant. This directed graph may be used to prioritise control loop maintenance by ranking the relative importance of the nodes in the system.

Methods of determining causality between variables on a plant-wide scale have been an active research topic with various papers being published in literature over the past few years. The focus of most of this research was root cause fault detection. The results of this work can be adapted as a prequel to

The main contribution of this paper is the integration of various known ranking, causal mapping and control loop assessment methods into a tool that can prioritize control loop maintenance on a plant-wide or even site-wide scale. In order to prioritize control loops it is necessary to identify control loops with the largest influence which are performing the worst while having the greatest impact on profitability.

* 1. General approach

As the objective is not only to identify control loops that have the greatest influence, but to prioritize loops for maintenance instead, performance metric is associated with each control loop. As many industrial operations already employ performance monitoring software the aim is to integrate the connectivity with predetermined performance scores. In addition to performance, safety and profitability triage metric should be associated with each control loop. Depending on the amount of information available this can be either categorical or numerical.

Under-performing control loops are identified and prioritized such that the loops which affect the most important variables downstream enjoy the most attention of the operator.

The structure of the paper is as follows: In Section 3 the ranking algorithm and its modifications will be discussed, Section 4 deals with the various methods for determining causality in order to generate a suitable adjacency matrix for the ranking algorithm, while Section 5 presents an example and Section 6 leaves some concluding remarks.

A good ranking algorithm would identify under-performing control loops and rank them in such an order that the control loop which is affecting the most important variables relative to the system will be given higher priority than a control loop which may be under-performing to a greater extent but affecting less important variables.

Mention benchmarks and deviations…

* 1. Ranking algorithm
     1. Original LoopRank algorithm

A modified form of the Google PageRank algorithm is sued to rank control loops based on their connectivity, interaction and importance scores (weights). This concept has been introduced by Farenzena & Trierweiler (2009) who dubbed the algorithm LoopRank when applied to the ranking of control loops.

In order to apply the method a directed graph defining the interactions between process variables is needed. For a review of directed graphs, see Narsingh (1974). A convenient method for representing a binary directed graph is an adjacency matrix as defined in Eq.(1).

|  |  |
| --- | --- |
|  | (1) |

The importance of a nodedepends on the importance of the nodes pointing towardsas displayed in Eq.(2).

|  |  |
| --- | --- |
|  | (2) |

In Eq.(2) is the set of nodes which have an incident edge to nodeand the edge weightensures that nodecontributes importance to nodein proportion to the extent to which it affects node.

If this system is expressed in matrix form the ranking problem reduced to the standard eigenvector problem of Eq.(3).

|  |  |
| --- | --- |
|  | (3) |

Thematrix is a normalized adjacency matrix such that each column sums to unity. The importance scores of the nodes are the elements of the normalized eigenvector corresponding to the eigenvalue of one in Eq.(3).

* + 1. Shortcomings addressed by modifications previously published

The ranking calculation presented above has the following shortcomings:

1. If the graph is disconnected non-unique rankings may occur.
2. If dangling nodes (nodes that do not point to any other nodes) are present, an adjacency matrix which is column-substochastic is generated.

If the graph is disconnected non-unique rankings may occurs as the eigenvector for a disconnected graph is *k*-dimensional (where *k* is the number of components) leading to ambiguity as to which basis eigenvector should be used to interpret importance. A remedy for this situation is to modify the normalized adjacency matrixby adding a matrix which is a normalized adjacency matrix for a fully connected system of the same size as the system being ranked. The modification is expressed in Eq.(4). The resulting matrix is used in the eigenvector calculations (Bryan & Leise, 2008).

|  |  |
| --- | --- |
|  | (4) |

A dangling node will result in the maximum eigenvalue being less than or equal to unity. In this case an appropriate ranking can still be achieved by using the largest positive (Perron) eigenvalue and accompanying eigenvector to calculate the importance scores (Bryan & Leise, 2008).

* + 1. Shortcomings addressed by new proposed modifications

Some shortcomings remain when the above mentioned ranking algorithm is applied to a chemical plant structure.

* + - 1. Input importance

Some process inputs may be more important to downstream processes than others. However, inputs to the plant serve as importance sources and hence their importance cannot be boosted by incident nodes. The importance of nodes can be modified to incorporate a contribution of the importance score of each variable generated when the connectivity of the plant is reversed as indicated in Eq.(5) – this effectively increases the importance of inputs which have a greater effect on downstream processes.

|  |  |
| --- | --- |
|  | (5) |

* + - 1. Nodes with one outward edge only

The normalization of thematrix will cause a loss of scale if any node with only one outward edge is present in the directed graph. This problem is not present if the node in question has more than one outwards directed edge as the edge weightings are automatically scaled in the normalization routine. An additional modification is therefore proposed whereby all nodes with a single outward directed edge are scaled by adding a dummy node and edge. The weight of the dummy edge constitutes a constant which brings the value of the other edge into perspective. The edge weight should typically be selected to be some small value. The dummy variables should be ignored when interpreting the results.

Adding dummy variables will result in the sum of all non-dummy variable nodes’ importance scores not summing to unity. However, as the interest is not in the absolute importance of each node – which is in any event not what the eigenvector analysis calculates – but only in the relative importance which is preserved this is not an issue.

* + 1. Edge weightings

<<Discussed later, figure out appropriate structure of paper>>.

The method includes modifications to previous graph-theoretic methods to align the ranking method with intuitions about the connectivity of controlled systems.

In the Google PageRank algorithm the value of an edge between nodes on a directed graph is considered to be a binary state. In order to refine the sensitivity by which control loops with the greatest sphere of influence can be isolated it is desired to assign some weight instead. These weights can be derived from the causality measured mentioned above. Different weighing strategies will be compared to binary mapping in order to find balance between robust results and engineering effort.

Knowledge-based methods for determining causality will generally be limited to generating a binary adjacency matrix. If knowledge-based methods are combined with data driven methods the main contribution of the knowledge-based methods will be to get the structure right while the data driven methods can be used to calculate appropriate weights for the connections.

The ranking algorithm is a generalized eigenvector problem once a suitable connectivity matrix has been identified. Setting up this matrix involves 1) determining the connectivity between process variables and 2) assigning weights and importance scores to the connections between process variables as well as the variables themselves.

The connectivity between process variables can be determined in at least two different ways: 1) Determining causality using data-driven methods and 2) defining connections by making use of known process topology (referring to physical and logical connectivity) information contained in P&IDs (pipeline & instrumentation diagrams) which are normally kept well organized and reasonably up to date.

* 1. Methods for determining causality

Methods for determining causality can generally be classified as either knowledge based, data-driven or as a hybrid between the two. The output is generally a connected digraph indicating connectivity as well as the direction of disturbance or control action propagation over the network.

A number of data-driven methods for determining causality between control loops have been reported in the past. A relatively new method called transfer entropy has been show to produce robust results even in the absence of observable time delays (Bauer et al., 2007). Another prominent method uses cross-correlation to estimate time delays in order to infer the sequence of events and therefore causality (Bauer & Thornhill, 2008). Assigning causality based on these methods follows statistical hypothesis testing whereby the apparent degree of correlation is compared to threshold values obtained by studying correlations between random signals of various sampling length and the desired confidence.

In data-driven methods historical data is analysed using various statistical methods in order to identify probable causality. Common methods include partial correlation, time delay estimation, nearest neighbours as well as the relatively new concept of transfer entropy first introduced by Schreiber (2000). The significance levels are compared to threshold values obtained by analysing surrogate random time series data and selecting a required minimum deviation, usually six sigma. The transfer entropy method has been shown to be the most robust compared to the cross-correlation and nearest neighbour methods and is also useful in the absence of noticeable time delays between variables (Bauer, 2005). Bauer (2005) proposed a modified transfer entropy calculation that allows for estimating the dead time. Shu and Zhao (2013) proposed an additional modification to this method that has been shown to be more accurate and has also reported on how the obtained time delays can be used to eliminate redundant connections.

<<Say something about the adjacency matrix and degrees of separation>>

Knowledge-based methods seek to determine causal connections by employing information on physical and logical connections coupled with reasoning algorithms <<mention Prolog topology work here>>. <<Give reference>> reported on the use of <<what open standard? CAPE something>> to derive plant topology from Pipeline & Instrumentation Diagrams (P&IDs) which are generally kept well organized and up to date.

Yim et al. (2006) reported on the development of a software package combining plant topology with data-driven performance assessment analysis. It is proposed that a similar hybrid approach is followed in order to generate connectivity matrices for the ranking problem using the data-driven methods mentioned above.

|  |  |
| --- | --- |
|  | (1) |

* 1. Example

The proposed method for the ranking of base layer control loop importance is demonstrated using the well-known Tennessee Eastman (TE) plant problem (Downs & Vogel, 1993). A model incorporating a decentralised control scheme proposed by Lyman and Georgakis (1995) and implemented by Chiang, Russell and Braatz (2000) was used to generate the results. A model incorporating a decentralised control scheme proposed by Ricker (1996) and available in the TEMEX archive (…reference…) was used to generate results. The TE plant was operated in Mode 1 (base case) as defined by Downs & Vogel (1993).

The connectivity metric was derived by using the Shu and Zhao (2013) modified transfer entropy method. In order to generate data useful for inferring causality, random noise was fed in the disturbance variable channels <<referring to the Simulink version which has these… otherwise does the standard problem have them as well?>>. The reference signals <<were / were not>> perturbed <<and why?>>.

The integrated squared error (ISE) was used to calculate performance scores for the different control loops. Rahman & Choudhury (2011) proposed a method whereby the importance of control loops can be ranked based on a loop interaction score (LI) obtained by calculating the ISE or IAE for steps in individual setpoints.

As it is desired that the method should not be dependent on explicit step testing in order to infer the relative importance of control loops it is suggested that the connectivity metrics be combined with performance scores in order to rank the importance of control loops from a maintanance priority perspective.

* 1. Future work

The application of other eigenvector ranking methods, mostly originating from the field of computer science, to the ranking of control loops in a chemical plant will be investigated. Two promising methods include semi-supervised ranking of graphs with rich metadata (Gao et al., 2010) and the use of weighted inter-cluster edge rankings for clustered graphs (Padmanabhan et al*.*, 2010).

To the end of developing a tool that is practically useful in industry, various case studies on actual plant data are planned in the near future. Close collaboration with process engineers and experts will ensure not only the accuracy and helpfulness of the method but also its user friendliness, especially as it relates to effort required to implement and maintain the system.

Eigenvector ranking methods applied to open loop data may be used as an aid to complement pairing selection using other methods such as the relative gain array (Skogestad & Morari, 1987).

Isolate importance sources and compare to overall importance scores to get relative strengths of inputs importance.

* 1. Conclusions

A method for ranking base layer control loop maintenance on a plant-wide scale is presented in this article. The method makes use of a modified LoopRank algorithm and requires a connectivity metric to be calculated using any of the discussed methods for determining causality.

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