

A METRIC FOR PATTERN-MATCHING APPLICATIONS TO TRAFFIC MANAGEMENT

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Abstract

This paper is concerned with signal plan selection. The paper outlines a system designed to assist the timely selection of sound congestion-reducing signal control plans; utilising on-line pattern matching. In this system, historical traffic flow data is continually searched, seeking traffic flow patterns similar to today's. If, in one of these previous similar situations, (a) the signal plan utilised was different to that being utilised today and (b) it appears that the performance achieved was better than the performance likely to be achieved today, then the system recommends an appropriate signal plan switch. The heart of the system is "similarity". Two time series of traffic flows (arising from two different days) are said to be "similar" if the distance between them is small; similarity thus depends on the metric or distance between the two time series. In this paper a simple example is given which suggests that utilising the standard Euclidean distance between the two sequences comprising *cumulatives* of traffic flow may be better than utilising the standard Euclidean distance between the two sequences of original traffic flow data. The paper also gives measured on-street public transport benefits which have arisen from using a simple rule-based (responsive) signal plan selection system, compared with a time-tabled, or fixed-time, signal plan selection system.

Keywords: Pattern matching, Signal plan selection, Cumulatives, Intelligent decision support.

1. Introduction

Travel is fundamental for the social, economic and cultural development of modern society; as an increasing population seeks ever-increasing mobility. This results in increasing congestion, especially in cities. How to address growing congestion in cities world-wide has been recognised as one of the major challenges in the 21st century, especially as currently more than 50% of the world's population now live in cities.

One of the tools that may be utilised to reduce congestion is the traffic control system. This paper considers pattern matching as part of an intelligent decision support (IDS) system aimed at helping to recall traffic signal control plans which worked well in the past (so that these successful plans may be re-utilised). The paper supposes that a list of signal control plans is already given and does not consider the generation or design of new signal plans.

1.1. Pattern-matching-based signal control plan selection

Given a list of signal control plans, the aim of a pattern-matching-based signal-plan selection system is (1) to recognise (quickly) those situations occurring today which have arisen (approximately) in the past, (2) to recall the specific signal plans which worked well in the past (if any), and (3) of those signal plans recalled, to recommend the most relevant plan change for implementation now. The central assumption is that

what happens next is (likely to be) what happened before.

The pattern-matching signal control system proposed here was designed in conjunction with the City of York. The stated aim of the City was *to reduce Park and Ride journey times without significantly damaging car travel times*; the policy tool agreed was *to switch signal timing plans suitably*. [The list of signal timing plans was here regarded as fixed; although some very limited signal timing plan “design” was undertaken.]

1.2 A very short technical context

Ritchie (1990) and Zhang and Ritchie (1994) design an integrated set of expert systems to process real-time data where learning possibilities are envisaged. Hernandez et al. (1999) introduced the TRYS system for building intelligent traffic management systems. Results of applying ramp metering strategies have been obtained by Haj-Salem and Papageorgiou (1995). A recent review of current techniques for utilising ITS in traffic management is provided by Papageorgiou et al (2007).

Broadly speaking, the work in this area addresses one or more of the following three questions.

Question 1 (concerning signal plan selection): for a given scenario, now, how should a signal plan be selected (from a given list or library of signal plans)?

Question 2 (concerning signal plan design): for a given scenario, how should new signal timing plans be designed for that scenario?

Question 3 (concerning adaptive or responsive control): how should signals adapt or respond (automatically) to traffic flows as these change?

The above questions are relevant over different time-scales: signal plan selection and responsive control should both ideally operate very quickly, while signal plan design must necessarily be much more laborious and hence slow.

It is natural to utilise pattern matching as an element in seeking to address question 1; and pattern matching may also have relevance to question 2. Felici et al (2006) seek to address both questions 1 and 2. Wiering et al (2004) outline a method of using pattern matching to help find good signal timings. Weijermars (2007) and Thomas et al (2008) present compendious and interesting analyses of traffic flow variations; various possible applications (including pattern matching applications) are mentioned but not discussed in any detail. They identify (a) seasonal variations with time scales of a week or more, (b) periodic variations at time scales of about 30 minutes and (c) noise. This paper is concerned mainly with question 1, concerning signal plan selection using pattern matching; but the paper also gives a brief description of a simple rule-based signal plan selection system together with on-street results of applying it. The paper makes a few comments on signal plan design and also outlines some technical data matters concerning the City of York.

There is a vast literature on question 3 concerning responsive signal control. The most well-known responsive rule for adjusting signal timings is the equisaturation rule devised by Webster (1958). Such rules, together with many others, are now utilised in the majority of

responsive signal control systems operating in the world today; aiming to approximately optimise signal timings by utilising (reasonably quick) responses to traffic flow changes.

1.2.1 Technical data management and the traffic flow data utilised

The City of York has an *Urban Traffic Management and Control* (or UTMC) system; this is designed to have published interfaces so as to aid the utilisation of all information flowing through the system. Every 5 minutes the UTMC system in York publishes the number of vehicles which have crossed each detector in the previous 5 minutes; the pattern-matching system was designed to utilise this “5-minute” traffic flow data.

1.2.2 Signal plan selection using pattern matching

Hauser, Scherer and Smith (2000) consider the opportunities for data mining to help design switching points in timetabled traffic control systems (the separate traffic control plans are given and fixed-time). Hegyi et al (2001) suggest using fuzzy logic based traffic control to manage non-recurrent congestion. De Schutter et al. (2003) extend this, combining case-based reasoning and fuzzy logic to develop a multi-agent evaluation system that can be used by traffic operators to analyse the expected performance of several potential (given) interventions. Zografos et al. (2002) developed an intelligent decision support system to reduce incident duration by integrating mathematical models, rules and algorithms with display technologies, allowing faster more accurate interventions. Almejalli et al. (2007) combine fuzzy logic, a neural network and a genetic algorithm to assist network operators by estimating the likely effectiveness of (given) interventions. Chen et. al. (2006) outline the design of a large-scale decision support system for Beijing.

1.2.3 Signal plan design

Kotsialos et al (2002) utilise non-linear optimal control theory to design motorway control systems; Hegyi (2004) outlines how model predictive control may be used to put together a coherent package of traffic control measures; van den Berg et al (2008a, b, 2009) and Shu Lin et al (2010) outline methods for designing interventions using mixed integer linear programming, within a model predictive control framework. (Thus far their main emphasis has not been on traffic signal control itself; however there are implications in their work for the design of traffic signal control plans.) Dealing specifically with traffic signal control in networks, Angulo et al (2011) suggest ways of optimising (and implementing) signal control plans using soft computing techniques and Smith (2009, 2010) and Smith and Mounce (2011) suggest a new way of designing fixed time signal plans suitable for different scenarios, using models. Smith (2006) applies bilevel optimisation to this problem; it would be interesting to compare this to approaches based on model predictive control.

1.3 Signal plan selection using rules: a real-life result

Reasonably simple rule-based signal plan selection methods avoid most of the operational delays which arise with a fully-fledged pattern-matching signal-plan change method; and even simple rules may yield significant benefits, as is suggested by the results shown here.

On the Hull Road in York general traffic is gated every day at one traffic signal by implementing a small green-time upstream of a bottleneck, moving a queue of general traffic heading for the City upstream to where the queue may be passed by buses.

The system currently utilised to select the gating plan is a simple time-table plan:

implement gating between 07:45 and 09:15.

In our demonstration this was changed to the following very simple rule-based signal plan selection system:

when the flow past a specified detector exceeds 68 vehicles in three consecutive 5-minute intervals then activate gating; and

when the flow past a specified detector is less than 68 vehicles in three consecutive 5-minute intervals then de-activate gating.

This responsive rule, and the gating strategy itself, were arrived at by model-based optimisation and some trial and error data modelling; this modelling tested seven different alternative plan selection rules off-line using flow data from the road network. (See Hodge et al (2010) for details.) The results obtained are shown in table 1.

	Average bus journey time	Standard deviation of bus journey time
Timetabled gating	180 seconds	91 seconds
Responsive gating	159 seconds	65 seconds

Table 1: On –street results for a.m. bus journey times with timetabled gating and rule-based, responsive, gating. Under the timetabled plan selection regime there were 508 journeys and under the rule-based responsive plan selection regime there were 61.

These results suggest that, compared to time-tabled signal plan selection, a simple responsive rule-based plan selection is likely to reduce the mean morning bus journey time; and is also likely to reduce the spread of morning bus journey times, improving bus journey time reliability.

2 A pattern matching system for signal plan selection

The plan selection system described here requires flows and signal plans to be stored so as to allow quick recall. An evaluation or performance index must also be calculated and stored. Pattern matching may then be used to determine a few of the most relevant or close matches (to today) from the past. The plan switch recommended then depends on (1) the *distances to the matches selected* (a small distance means that this past day was very similar and so relevant to today) and (2) the *performance indices* (PIs) of the corresponding (flow pattern, signal plan) pair.

2.1. Examples of performance indices.

There are very many possible performance indices or PIs. The ones we agreed with the City of York Council, and which led to the results in section 1.3 above, were:

- average public transport journey time along the Hull Road and
- standard deviation of the public transport journey time along the Hull Road.

Another example of a PI is:

- average journey time for cars.

Clearly, there are interactions between the PIs chosen, the interests of the local authority and the data gathering facilities available. The City of York has a great interest in improving and

monitoring bus performance so as to encourage car travellers to park their cars on the outskirts of York and use Park and Ride buses to reach the historic City.

2.2. Suggested technique for signal plan selection.

The aim is to recover those flow patterns which have the best (smallest) PIs on the days most similar to today. So suppose that we have found, in the historical record, the k flow patterns
 flow pattern 1, flow pattern 2, flow pattern 3, . . . , flow pattern k
 which are closest to today's flow pattern so far; that is to flow pattern 0. Suppose that we also have recovered the corresponding signal plans utilised; let signal plan n be the plan utilised with flow pattern n . Suppose also given the corresponding performance indices or PIs; with $PI(n)$ being the PI associated with the (flow pattern n , signal plan n) pair. For $1 \leq n \leq k$, let

$$R(n) = [PI(0) - PI(n)]$$

be the estimated reduction $R(n)$ in the PI which would arise if plan 0 was switched to plan n and

$$Q(n) = R(n)/\text{dist}[\text{flow pattern } n, \text{flow pattern } 0].$$

It would then be reasonable to continually suggest for implementation plan n^* where n^* maximises $Q(n)$ (for $1 \leq n \leq k$), provided $Q(n^*)$ exceeds an agreed positive threshold th . (It would not be good to change plans for diminutive estimated rewards.) R stands for "reduction" and Q stands for quotient or ratio and estimates the reward / risk ratio, assuming that reward is proportional to the predicted decrease in the PI and risk is proportional to $\text{dist}[\text{flow pattern } n, \text{flow pattern } 0]$.

Figure 3 in appendix 1 is designed to be a user-friendly representation of this process; so as to aid the decision-maker. In figure 3 the estimated reductions in the PI are shown on the vertical axis and the distance of the historical cases to today's flow pattern are shown on the horizontal axis. To change to the plan on day m one would wish to see $R(n)$ large (predicting a large benefit from the switch) and a small $\text{dist}[\text{flow pattern } n, \text{flow pattern } 0]$ (giving confidence); or a large $Q(n)$.

The Intelligent Decision Support system would then continually send simple messages to transport operators always recommending plan n^* where

$$Q(n^*) \geq Q(n) \text{ if } 1 \leq n \leq k; \text{ and also } Q(n^*) \geq th > 0. \quad (1)$$

Plan n^* could be automatically implemented if the system had generated sufficient trust and facilities are available. To build confidence the initial threshold th might be large, to be reduced over time. There are natural generalisations: it would perhaps be natural to let F be any convex increasing positive function and to put:

$$Q_F(n) = F\{[PI(0) - PI(n)]\}/\text{dist}[(\text{flow pattern } n, \text{flow pattern } 0)].$$

The continual recommendations would then still be determined by (1) but with Q_F instead of Q . A steep F will recommend few plan changes and if F is the identity then $Q_F(n) = Q(n)$ and we have the previous scheme.

To do the selection in a short period of time it is important to be able to search very large databases very quickly.

2.3 Fast large k-NN searches

Standard k -NN pattern matching is known to be a robust and flexible method that allows the pattern matcher to be updated continuously. However one drawback is the speed of the standard method, which typically becomes slow for large problems.

An efficient version of k-NN, based on the Advanced Uncertain Reasoning Architecture (AURA) (Austin et al., 1998; Hodge and Austin, 2005), may be used to overcome this problem. AURA is a library of methods and applications built on binary neural networks and designed for high speed search and match operations in large data sets; AURA is thus fast, scalable and compact. Data may include (1) flow and occupancy data from a number of loop detectors at signals and elsewhere, (2) travel time data from a number of bus stops or buses, and (3) other data such as travel times estimated from GPS data.

For each 5-minute period, on each day, the above data may be concatenated into a single current “5-minute attribute value vector” and then matched against past “5-minute attribute value vectors”.

Derived data, such as the flow/occupancy ratio (see Han et al., (2009)), may also be utilised. Further, it is also natural to utilise road works data, special events data, and weather data. The purpose of using this additional data is to add precision to the matching of past traffic patterns to today’s patterns. For example it would be natural on a Race Day at York to look only at previous Race Days when seeking matching traffic patterns from past. Finally it would also be natural to use data derived from running offline models.

2.2 Flows or cumulative flows?

Pattern matching in this context requires the dis-similarity or distance between two time series. The Euclidean distance between two such time series

$$u = \{u_1, u_2, u_3, \dots, u_n\} \text{ and } v = \{v_1, v_2, v_3, \dots, v_n\}$$

(each representing flows in each 5-minute time period stretching between times t_1 and t_{n+1}) is

$$d(u, v) = [(u_1 - v_1)^2 + (u_2 - v_2)^2 + (u_3 - v_3)^2 + \dots + (u_n - v_n)^2]^{1/2}. \quad (2)$$

When the time series u and v above are time series of *flows*, with co-ordinates representing the flows in each 5-minute time period stretching between times t_1 and t_{n+1} , there is always the alternative of using use cumulative flows instead. To do this, we first calculate the corresponding time series of cumulative flow values

$$U = \{U_1, U_2, U_3, \dots, U_n\} \text{ and } V = \{V_1, V_2, V_3, \dots, V_n\}$$

by putting $U_1 = u_1$, $U_2 = u_1 + u_2$, $U_3 = u_1 + u_2 + u_3$, etc. And only then use Euclidean distance.

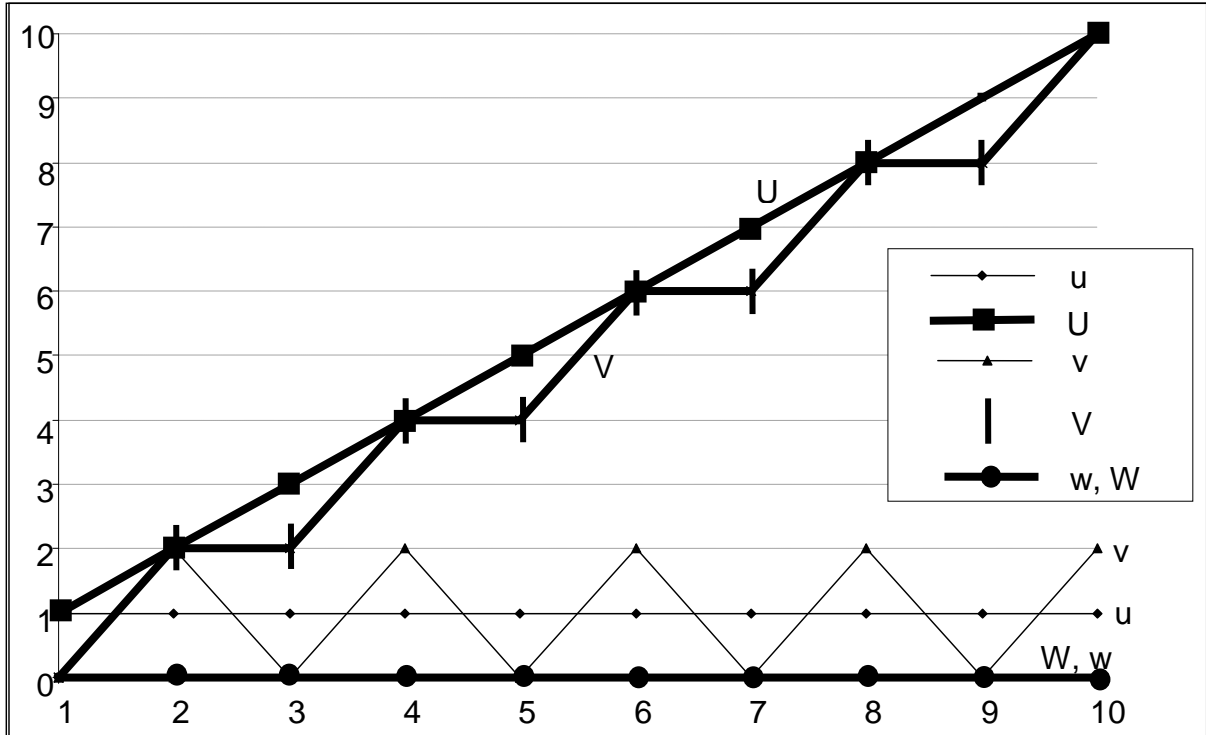


Figure 1. Time series, u , v and w and the corresponding cumulative flow series, U , V and W .

Consider the following three time series comprising 10 consecutive 5-minute flow values:

Time series 1: $u = (1, 1, 1, 1, 1, 1, 1, 1, 1, 1)$, so that $U = (1, 2, 3, 4, 5, 6, 7, 8, 9, 10)$.

Time series 2: $v = (0, 2, 0, 2, 0, 2, 0, 2, 0, 2)$, so that $V = (0, 2, 2, 4, 4, 6, 6, 8, 8, 10)$.

Time series 3: $w = (0, 0, 0, 0, 0, 0, 0, 0, 0, 0)$, so that $W = (0, 0, 0, 0, 0, 0, 0, 0, 0, 0)$.

All six time series are shown in figure 2; u , v , w are the given time series of flows and U , V , W are the corresponding cumulatives. Using the Euclidean distance formula directly,

$$d(u,v) = n^{1/2} = d(u,w).$$

On the other hand, using the Euclidean distance on the sequences of cumulative flows:

$$d(U,V) = [1/2n]^{1/2} \text{ and}$$

$$d(U,W) = [n(n+1)(2n+1)/6]^{1/2} = [(n+1)(2n+1)/3]^{1/2} [1/2n]^{1/2}.$$

So that, as $n = 10$,

$$d(U,W) = [(n+1)(2n+1)/3]^{1/2} d(U,V) = [11.21/3]^{1/2} d(U,V) = [77]^{1/2} d(U,V) > 8 d(U,V).$$

Thus, for $n = 10$ and for these three time series u , v , and w , the Euclidean distance function indicates that v and w are equidistant from u . In contrast, Euclidean distance indicates that W is more than eight times as far away from U as V is. It is then natural to ask: which time series is more significant or “better” for matching in this traffic flow context? Plainly nearest neighbours may well vary according to the way the Euclidean metric is utilised.

The original time series of 5-minute flows may be expected to give more information more quickly when there is a sudden change caused by a sudden serious accident; on the other hand it may exaggerate traffic impacts when (for example) everything is 5 minutes late. Cumulative flows may be better at detecting such a 5-minute shift and also may be better at diagnosing rather more long running and subtle changes brought about on a single day by a “minor” blockage leading rather gradually to problems, re-routing caused by a rather distant accident or minor breakdowns in signal operation. Cumulative flows must also be better at detecting more long term systematic changes such as an increase in the flow of tourists or the number of

school runs at certain times of year. It may be that, for a given input sequence u of five-minute flows, the “state” of the link flow at a particular time might, for most purposes, be better measured by the corresponding cumulative flow sequence U .

These considerations give rise to other possible metrics, bearing in mind that 5-minute flows from a long time past will be irrelevant. (Figure 1 just looks at 10 values; 50 minutes’ worth of 5-minute periods.) So consider sequences of cumulatives over windows of various not-too-long lengths t (where t is a multiple of l) ending at the current time t_0 (also a multiple of l). To make this precise we choose a not too large number T ($T = 10$ in the above illustration) and agree that:

$t_0 =$ now, e.g. 4pm on Thursday 1st October 2011 (t_0 is a multiple of l)

$l =$ duration of the time period of the data aggregation, e.g. 5 minutes in UTMTC,

$T =$ duration of the moving time series window stretching backwards from t_0 to $t_0 - T$ (all cumulatives utilised lie within this window and T is a multiple of l),

$f_x(u) =$ flow past location x during time period u stretching from u to $(u + l)$ (where u is a multiple of l), and

$F_x^{t_0}(t)$, the cumulative flow in the period $[t_0 - t, t_0]$ is given by:

$$F_x^{t_0}(t) = \sum_{u \in \{t_0-t, t_0-(t-l), \dots, t_0-l\}} f_x(u) du$$

for the values of $t = l, 2l, 3l, \dots, T$. (each t here is a multiple of l .)

$F_x^{t_0}(t)$ is the total or cumulative flow past location x between time $t_0 - t$ and time t_0 . We then consider the following sequence of cumulatives over the whole window of duration T :

$$F_x^{t_0}(l), F_x^{t_0}(2l), F_x^{t_0}(3l), \dots, F_x^{t_0}(T).$$

Figure 2 illustrates cumulative flows on the moving time series window; clearly T needs to be carefully calibrated in order to capture the correct time scale for detecting significant events. It would be natural to have copies of this system with different values of T to capture differing time-scales of different traffic phenomena. ($T = l$ yields the original distance function (2).)

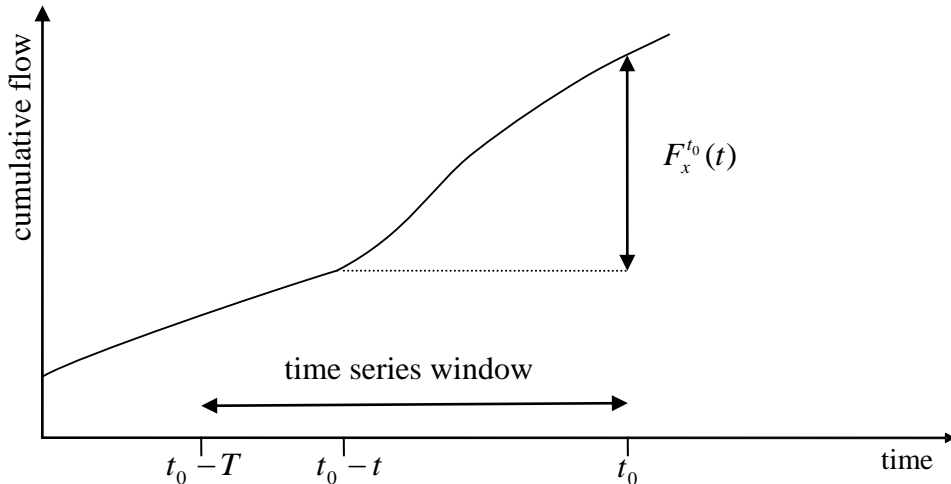


Figure 2. The moving time series window for flow at location x

Let X denote the set of locations x at which detectors are located and let $F^{t_0} = (F_x^{t_0})_{x \in X}$ denote the vector of cumulative flow functions looking backwards from time t_0 . Then define the distance between cumulative vector flow profiles F^{t_0} and F^{t_1} as follows:

$$d(F^{t_0}, F^{t_1}) = \sqrt{\sum_x \sum_{t=l}^{t=T} |F_x^{t_0}(t) - F_x^{t_1}(t)|^2} \quad (2)$$

where t_0 and t_1 belong to different days and the time summation (over t) in (2) increments in units of l . A natural “exponential decay” version of (2) would be:

$$d(F^{t_0}, F^{t_1}) = \sqrt{\sum_x \sum_{t=l}^{t=\infty} e^{-kt} |F_x^{t_0}(t) - F_x^{t_1}(t)|^2}$$

where $k > 0$. This distance would be very quick indeed to calculate as previous values may be utilised in a simple updating formula, and it may prove to be accurate enough.

3. Conclusion

A pattern matching system has been outlined; this has been designed to help the intelligent selection of signal timing plans, with particular application in the City of York (or any other City with a UTMC system). The system utilizes the distance between two time series of traffic flows; and two ways of defining this distance have been given. (One is the standard Euclidean distance between the two sequences of raw 5-minute data and the other is the standard Euclidean distance between the two corresponding sequences of cumulatives). A simple example has been given which demonstrates that the distance which utilizes cumulatives may be the better of the two. Ways of using the pattern-matching results are outlined and a possible user-friendly presentation of these results is given in the appendix; see figure 3. On-street results from a real life test of a rule-based signal plan switching system have also been presented.

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APPENDIX. An intuitive way of representing candidate signal plan changes.

A way of representing the pattern matching results in a compact intuitive way is shown in figure 3. Five historical (flow pattern, estimated PI reduction) pairs are represented by white triangles. These are continually plotted (each 5 minutes say) and move against the background of a fixed cone of acceptable improvement with vertex at the current (flow pattern, 0) pair (the black triangle). The y-coordinate of triangle 4, for example, gives the estimated reduction in the PI which would arise if the current plan was changed to that utilized when flow pattern 4 occurred in the past.

The cone of acceptable improvement displays a trade-off between choosing a close match to the flow today so far (giving confidence, like flow 1 or 2 here which are very like today) and choosing a plan which gave a small PI in the past, and hence yields a large estimated reduction in the PI (like the plans associated with flow pattern 4 or 5). The plan associated with flow pattern 4 looks the best bet here. If the plan corresponding to flow pattern 4 is the same as the plan corresponding to flow pattern 5 then this diagram would strongly support that plan. Such perceptions are assisted by the picture shown here in figure 3. Arrows might be added to indicate the likely direction of movement of each triangle; extrapolated from past results.

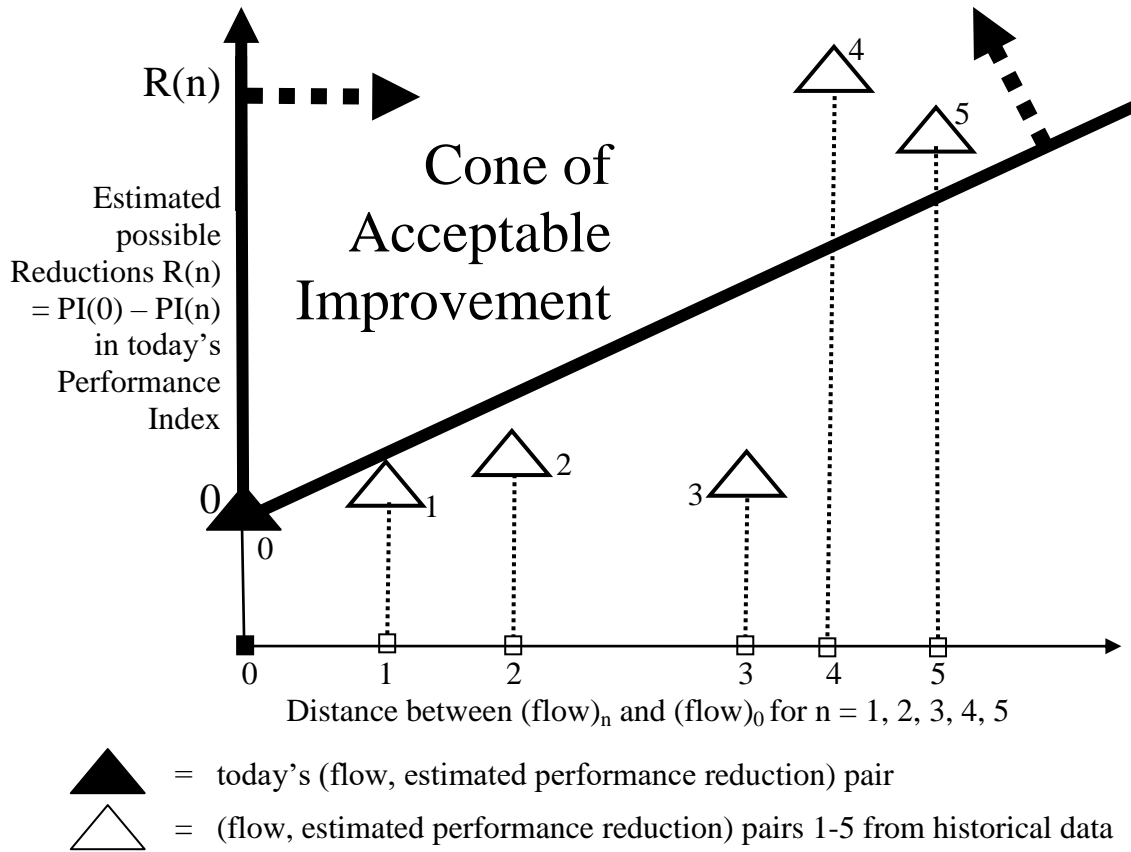


Figure 3. Five historical (flow, performance reduction) pairs where the flow pattern is close to today's flow pattern. The cone of acceptable improvement contains pairs with associated reasonable signal plans; here only (flow, performance reduction)₄ and (flow, performance reduction)₅ have reasonable associated signal control plans.