Critical node selection method for efficient Max-Pressure traffic signal control in large-scale congested networks

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SHORT SUMMARY

Decentralized signal control of congested traffic networks based on the Max-Pressure (MP) controller is theoretically proven to maximize throughput, stabilize the system and balance queues for single intersections under specific conditions. However, its performance for wide implementation requires further attention. Increased implementation cost related to queue monitoring in controlled intersections reduces MP applicability. Aiming at reducing this cost, we propose a strategy for identifying the most critical network intersections to introduce MP control, with the aim of reaching high efficiency without a full-network implementation. The proposed selection process is based on node congestion and queue variance data. A modified version of Store-and-Forward dynamic traffic model is used to emulate spatio-temporal traffic evolution in a large-scale network with more than 500 intersections and evaluate system performance for different MP node layouts. Results show that more than 90% of the improvement observed when all network nodes are controlled can be achieved by controlling only 20% of nodes, selected via the proposed strategy, thus significantly reducing implementation cost. The impact of MP application in network traffic characteristics is demonstrated through detailed analysis.

Keywords: adaptive traffic signals; decentralized control; Max-Pressure; cost efficiency; critical nodes; Store-and-Forward.

1. INTRODUCTION

Continuing urbanization of modern societies necessitates measures to maximize serving capacity of traffic networks, in order to satisfy the increasing travel demand. Adaptive traffic signal control systems carry significant potential in reaching this objective due to their ability of dynamically adjusting green/red light based on the prevailing traffic conditions. Max-Pressure (MP) decentralized controller, initially proposed for packet scheduling in wireless communication networks by (Tassiulas & Ephremides, 1990), was formulated as a signalized intersection controller through the works of (Varaiya, 2013b), (Varaiya, 2013a) (Wongpiromsarn, Uthaicharoenpong, Wang, Frazzoli, & Wang, 2012), (Zhang, Li, Feng, & Jiang, 2012) and was theoretically proven by (Varaiya, 2013b) to stabilize queues and lead to maximum network throughput under specific conditions. The stability guarantee, together with MP's independence from any a priori knowledge of traffic demand and its decentralized nature, render it a promising and easily applicable control strategy for signalized networks facing congestion. Nevertheless, in networks with many intersections and limited storage capacity, the performance of MP is not well investigated. The effects of network implementation of adaptive signal control strategies have been investigated for a specific network via simulation in (Salomons & Hegyi, 2016). Also, since the seminal paper of (Varaiya, 2013b) on

MP assumed point queues and no spill-backs, it is important to investigate the effect that relaxation of these assumptions might have in network performance.

Despite the increased research interest in MP (e.g. see the more recent works of (Gregoire, Qian, Frazzoli, De La Fortelle, & Wongpiromsarn, 2014), (Kouvelas, Lioris, Fayazi, & Varaiya, 2014), (Le et al., 2015), (Manolis, Pappa, Diakaki, Papamichail, & Papageorgiou, 2018), (Mercader, Uwayid, & Haddad, 2020)), its applicability remains low due to its high installation and maintenance cost related to the required traffic measurement equipment, which is proportional to the number of controlled intersections. However, little to no research has been done to investigate the importance of the number and topology of the MP controlled intersections in the overall system performance, with most efforts assuming global network installation. This study aims at investigating how MP performance is affected by the number and topology of the controlled intersections and proposes a strategy to identify critical intersections for MP control, by targeting a set of node characteristics including occupancy and variance of queues of surrounding links, as well as duration of high node congestion. These characteristics directly relate to the objectives of MP controller and can be reliable indicators of high potential performance improvement through MP control. A modified version of a queuing-based traffic model is used to evaluate a set of different MP controller layouts with different numbers of network nodes involved, selected either randomly or based on the proposed strategy. Results of a detailed analysis of the performance changes induced by MP in the network and node level are presented below.

2. METHODOLOGY

The Max-Pressure Controller

The MP traffic controller, as described by (Varaiya, 2013b), is a feedback-based signal control algorithm that modifies green time allocation among competing phases of independent intersections based on real-time queue measurements of upstream and downstream links. The version utilized here is similar to the one presented in (Kouvelas et al., 2014), briefly explained hereafter.

A traffic network is represented as a directed graph (N,Z) consisting of a set of links $z \in Z$ and a set of nodes $n \in N$. At any signalized intersection n, I_n and O_n denote the sets of incoming and outgoing links, respectively. The cycle time C_n and offset, which enables coordination with the neighboring intersections, are pre-defined and not modified by MP. Intersection n is controlled according to a pre-timed signal plan, which defines the sequence, configuration and initial timing of a fixed number of phases that belong to set F_n (including the fixed total lost time L_n). During activation of each phase $j \in F_n$, a set of non-conflicting approaches v_j (i.e. connections between pairs of incoming-outgoing links of the node) get right-of-way (green light) simultaneously. The saturation flow of any link z, denoted as S_z, refers to the maximum possible flow that can be transferred to downstream links, depending on link and intersection geometry. The turning ratio of an approach between links $i-w$, where $i \in I_n, w \in O_n$ is denoted as $\beta_{i,w}$ and refers to the fraction of the outflow of upstream link i that will move to downstream link w. The present version of MP assumes that turning ratios are known to the controller. However, it has been shown that control effectiveness is not deteriorated if turning ratios are estimated (see (Le et al., 2015)). By definition, the following relation stands for every node n,

$$\sum_{j \in F_n} g_{n,j}(k_n) + L_n = (\text{or} \leq)\ \ C_n \tag{1}$$

where $k_n = 1,2,\ldots$ is the discrete-time control cycle index of node n, and $g_{n,j}$ denotes the green time duration of phase j at cycle k_n. The inequality may apply in cases where long all-red phases are imposed for any reason (e.g. gating).

Phase sequencing remains unchanged by the present version of the controller. Consequently, all phases are activated (get green) for a minimum time, in the same ordered sequence, within every cycle. This is translated to the following constraint for every node n,

$$g_{n,j}(k_n) \geq g_{n,j,\min}, j \in F_n, \tag{2}$$

where, $g_{n,j,\min}$ is the minimum green time required for phase j of node n, long enough to serve the respective pedestrian movements. The system state is represented by the average number of vehicles inside incoming and outgoing links z of node n (queues) during control cycle k, denoted as $x_z(k)$. Assuming that real-time measurements (or estimates) of turning ratios and queues around the controlled intersection are available, the pressure $p_z(k)$ of every incoming link $z \in I_n$ of node n based on control cycle k is computed as the weighted difference between occupancy levels of any link and its downstream links, as

$$p_z(k) = \left[\frac{x_z(k)}{c_z} - \sum_{w \in O_n} \frac{\beta_{z,w} x_w(k)}{c_w} \right] S_z, \quad z \in I_n \tag{3}$$

where c_z is the storage capacity of link z. The normalization of queues by dividing by the storage capacity aims at considering the link length and number of lanes, so that pressure indicates link spill-back probability. By multiplying by saturation flow, pressure is weighted according to link service rate. Essentially, pressure depicts a probability of efficient green time utilization (vehicles actually crossing the node) based on the congestion level difference between every upstream and all its downstream links. High pressure indicates higher potential in traffic production, i.e. several vehicles waiting to be served and enough available space in downstream links to receive them. Low or close to zero pressure indicates high probability of a downstream queue to reach its storage capacity and spill-back in the following cycle (gridlock), or small queue of vehicles upstream. We should note that negative pressure is meaningless, so the constraint $p_z(k) \geq 0$ must hold.

Pressures of all incoming links of the intersection are calculated according to queue measurements at the end of every control cycle and used for updating greens for next cycle. Equation 3 is applied for all $z \in I_n$ and pressures for all incoming links of node n are computed at the end of every control cycle. Then, the pressure of each stage j is defined as the sum of the pressures of all links belonging to the stage, as follows.

$$P_{n,j}(k) = \max \left\{ 0, \sum_{z \in v_j} p_z(k) \right\}, \quad j \in F_n \tag{4}$$

Phase pressures are then used as weights for the distribution of the total available green time.

Green time calculation

After pressure values $P_{n,j}$ are available for every phase $j \in F_n$ of intersection n, the total amount of effective green time,

$$G_n = C_n - L_n = \sum_{j \in F_n} g^{\star}_{n,j}, \quad n \in N \tag{5}$$

is distributed to the phases of node n according to pressure values. In the above equation (5), $g^{\star}_{n,j}$ denotes the green of phase j at intersection n according to the static fixed-time control plan. It holds that $g^{\star}_{n,j} \geq g_{n,j,\min}, \forall j \in F_n$.

There are several different approaches that have been proposed regarding green time calculation, some of which also include phase activation based on pressures. In this version, since phases are activated in a strictly defined and non-changing order with a guaranteed minimum green time, green time $\tilde{g}_{n,j}(k)$ is assigned to every phase j proportionately to the computed pressures, as follows.

$$\tilde{g}_{n,j}(k) = \frac{P_j(k)}{\sum_{i \in F_n} P_i(k)} G_n, \quad j \in F_n \tag{6}$$

Eq. (6) provides the raw green times calculated according to MP control logic. However, these values cannot be immediately applied, because they need to comply to constraints of minimum and maximum green time duration and integer values. Therefore, an additional step is added in the process, whose objective is to translate outputs of eq. (6) to practically applicable green times $G_{i,j}$. This is done by solving online the following optimization problem (similar to (Diakaki, Papageorgiou, & Aboudolas, 2002)):

$$\begin{aligned}
\underset{G_{n,j}}{\text{minimize}} \quad & \sum_{j \in F_n} \left(\tilde{g}_{n,j} - G_{n,j}\right)^2 \\
\text{subject to} \quad & \sum_{j \in F_n} G_{n,j} + L_n = C_n \\
& G_{n,j} \geq g_{n,j,\min},\ j \in F_n \\
& \left|G_{n,j} - G^p_{n,j}\right| \leq g^R_{n,j} \\
& G_{n,j} \in \mathbb{Z}^+ \\
& \forall j \in F_n
\end{aligned} \tag{7}$$

According to the above formulation, the applicable green times $G_{n,j}$, for every phase $j \in F_n$, should be as close to the controller-defined greens $\tilde{g}_{n,j}$ as possible, while satisfying a set of constraints. The first constraint states that eq. (1) must always hold, therefore the sum of the updated feasible green times plus the total lost time L_n should be equal to cycle C_n. The second constraint ensures minimum green duration $g_{n,j,\min}$ (see eq. 2). In order to avoid potential instability due to large changes in the signal timing happening too fast, we impose an upper threshold to the allowed absolute change of phase duration between consecutive cycles. This is expressed in the third constraint, where $G^p_{n,j}$ denotes the applied green times of the previous cycle and $g^R_{n,j}$ is the maximum allowed change of the duration of phase j between consecutive cycles. Finally, feasible green times must belong to the positive integers set. This type of integer quadratic-programming problem can easily be solved by any commercial solver fast enough to allow online solution after every control cycle. The optimal values of variables $G_{n,j}, \forall j \in F_n$, are the new feasible greens of phases of node n, which will be applied in the next cycle. The above process, which is repeated at the end of every cycle, is only a function of traffic information around the intersection, without any information about the rest of the network. It only requires real-time queue measurements of the adjacent intersections and respective turning ratios.

Critical node selection method

This study aims at investigating the network-wide effectiveness of decentralized MP control when only a fraction of the network intersections are controlled, which would drastically decrease implementation cost. Therefore, a classification method to identify critical network nodes in terms of MP control is developed. Thinking that MP aims at stabilizing and balancing the queues around nodes, an intuitive hypothesis is that controlling intersections experiencing high levels of congestion and variance of queues forming at surrounding links would benefit more by MP control. On this basis, we propose the following node selection process, where congestion level and variance of queues are defined as follows:

Step 1: Traffic simulation of the network with expected demand (or traffic data collection) is performed with only fixed-time signal control and peak-period results are extracted.

Step 2: For every network node n and for a pre-defined peak-period P, the number of control cycles N^n_c during which n is highly congested is counted. Binary function $C(k)$ dictates that any node n is considered highly congested during cycle k if average queue of any incoming link

$z \in I_n$ during k is higher than a percentage of its storage capacity. In the current analysis, we set this to value to 80% as this significantly increases the possibility for spill-back occurrence (see (Geroliminis & Skabardonis, 2011). Therefore,

$$N_c^n = \sum_{\forall k \in P} C_n(k), \tag{8}$$

$$C_n(k) = \begin{cases} 1, & \text{if} \quad \frac{1}{t_k}\sum_{i=(k-1)t_k+1}^{kt_k} x_z(i) \geq 0.8c_z, \quad z \in I_n \\ 0, & \text{else} \end{cases} \tag{9}$$

where t_k is the number of discrete time-steps composing one control cycle.

Step 3: Nodes remaining congested for more than $\hat{N}$ cycles of the defined peak period are candidates for MP controller, i.e. nodes belonging to set $S_{MP} = \{n \in N | N_c^n > \hat{N}\}$, where $\hat{N}$ is a user-defined case-dependent threshold. All remaining nodes are disregarded.

Step 4: For every node $n \in S_{MP}$, we calculate two quantities: m_1^n which expresses the average congestion experienced by node n during peak-period, computed as

$$m_1^n = \frac{1}{t_p} \frac{1}{\|I_n\|} \sum_{i \in T_P} \sum_{z \in I_n} \frac{x_z(i)}{c_z} \tag{10}$$

where T_P is the set of time-step indices corresponding to the peak period and t_p is the size of this set, i.e. $t_p = \|T_P\|$, and m_2^n, which expresses the average variance of the queues forming around a node during peak-period, computed by

$$m_2^n = \frac{1}{t_p} \sum_{i \in T_P} \mathrm{var}\big(X_z^n(i)\big) \tag{11}$$

where $X_z^n(i) = \{x_z(i)/c_z | \forall z \in I_n\}$ is the set of normalized queues of all incoming links z of node n at time step i.

Step 5: We create the set of MP controlled nodes by selecting all nodes out of set S_{MP}, for which $m_1^n > M_1$ and $m_2^n > M_2$, where M_1 and M_2 are user-defined thresholds. These will determine the number of nodes that will be selected, so they can be defined according to the approximate number of nodes that we wish to include in the MP control layout. Short variations around the selected values do not significantly influence the results.

3. RESULTS AND DISCUSSION

A modified version of link-based Store-and-Forward (SaF) traffic model (see (Tsitsokas, Kouvelas, & Geroliminis, 2021)) is used as a simulator to evaluate a set of different MP node layout scenarios for a realistic case study. A replica of Barcelona city center traffic network is used and traffic is simulated for a realistic Origin-Destination demand matrix and fixed-time traffic signal plan for all controlled intersections. The network is composed of 1570 links and 933 nodes, out of which 565 represent signalized intersections with signal control cycles of 90 sec.

Firstly, sets of randomly selected MP node layouts are tested to create a benchmark and compared to those constructed via the proposed selection strategy, in terms of total travel time. Different network MP penetration rates are tested in both cases. The fixed-time control (FTC) case and the full-network MP application to all eligible nodes (labelled as '100%') are used as reference cases. The selection strategy is applied in two modes: direct MP node selection, based on selection measures computed from FTC results; and incremental node selection in steps of 5% nodes (27 nodes), where measures are recalculated in every step from MP simulation results of the previous step.

Table 1: Performance measures for different MP node percentages selected by the proposed method. The values show percentile difference with respect to FTC scenario (no MP control).

Fraction of MP nodes	**100%**	**10%**	**20%**	**30%**
Total travel time (VHT)	-30.00%	-24.14%	-27.45%	-22.64%
Mean VQ length (veh)	-41.53%	-36.09%	-38.54%	-33.11%

A 6-hour simulation with a 15-minute warm-up period and 2-hour peak is executed for all tested scenarios. Turning ratios of SaF model, that reflect routing decisions, are dynamically recalculated in regular intervals based on time-wise shortest paths, that are calculated based on model-estimated link speeds. An impact analysis of MP control schemes is performed in the node level by comparing mean and variance of node queues and high congestion duration, i.e. the defined selection measures, before and after the MP application.

Figure 1 shows the utilized network, partitioned in three homogeneous regions, and indicates the locations of MP nodes used in every scenario, when node assignment is done in one step based on FTC case results. A 2-hour peak-period (1.5 to 3.5 h) composed by 80 control cycles is defined for the selection process. Different threshold values M_1 and M_2 are set for every homogeneous region, and combined with congestion threshold $\hat{N}$, result in a target node percentage (10%, 20% etc.). It is clear that as congestion has strong spatial correlations due to queue propagation, in most cases the chosen intersections form a sequence of nodes in arterial of the network. Figure 2 depicts the performance change of all tested scenarios, in terms of total travel time in vehicle-hours travelled (VHT), with respect to the FTC case (no MP control). Ten randomly selected MP node sets are evaluated for every target percentage of network nodes controlled by MP, whose performance is represented by boxplots, while results of MP node sets generated by the proposed selection strategy are depicted by rhombuses for the one-step (direct) assignment mode, and by squares for the incremental assignment mode. Firstly, MP is demonstrated effective in improving network traffic performance in all cases, even with random node selection. However, it is evident that targeted selection is crucial for better MP performance, as all random cases result in significantly smaller performance improvement compared to the corresponding cases of node selection, showing the proposed selection method effective in identifying critical nodes for MP application. We observe that by applying MP in only 20% of eligible network nodes, we achieve around 27% travel time improvement compared to FTC, while in case of all nodes controlled, we only achieve an additional 3%. Therefore, we achieve close to maximum performance by only one fifth of MP implementation cost. Detailed results are shown in Table 1 for the total travel time and the mean virtual queue size (vehicles that are stored in the origin sources of demand generation).

Regarding the direct vs. incremental MP node assignment, we observe that both lead to similar performance, with the direct assignment being slightly more efficient. This observation may indicate that MP installation can cause traffic changes that affect other network nodes, especially in a dynamic environment where travellers adjust their paths accordingly to current network conditions. Further research is required in this direction.

In a more detailed analysis of the impact of MP controller to node performance, and with the aim of assessing the node selection criteria of the proposed method, figure 4 depicts the node classification according to measures m_1, m_2 and N_c before and after the MP assignment and application, i.e. for the cases 10% and 20% nodes, for the selected peak-period of 2 hours. The first row of figures shows the situation before MP (FTC) while the second shows the situation after MP is applied to the selected nodes. Selected nodes are colored in blue and non-selected nodes in light green. We observe that node queue variance m_2 is reduced for many of the selected nodes,

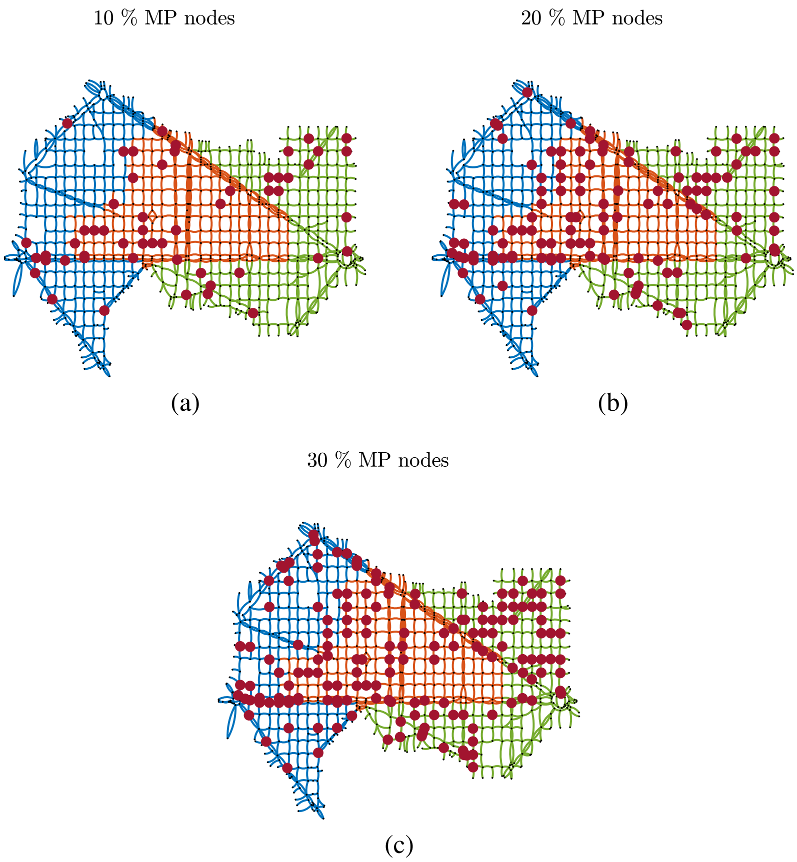


Figure 1: Plan of the studied network with selected MP nodes visualization: (a) Case 10%; (b) Case 20%; (c) Case 30%.

while and duration of high congestion (N_c) also drops for many selected nodes, though not for all. Moreover, figure 3 presents the cumulative distribution functions (CDF) of the average change in the same three measures among all MP and non-MP nodes before and after MP implementation, for three node layouts. Table 2 lists the mean values of change for all measures and cases. We can see from both, that the majority of nodes receiving MP controller tend to significantly reduce their variance and high congestion time, with very few nodes experiencing increase. Mean node occupancy, quantified by m_1, also increases in many nodes, but this may indicate that several MP nodes actually increase their occupancy because more vehicles are able to be served due to the increase of system capacity induced by MP.

The system seems to increase its service capacity by introducing MP controllers, even to fraction of network intersections, as shown in figure 5. In 5(a) the Macroscopic Fundamental Diagram (MFD) of production vs. vehicle accumulation is plotted for all cases, where all MP curves are above the FTC, meaning that the network manages to increase its serving capacity, reaching higher values of production for the same demand without increasing congestion level. The same is also evident by the increased maximum vehicle accumulation (see fig. 5(d)) compared to FTC case, without significant drop in the respective production. Consequently, virtual queues forming outside the network reduce significantly in MP cases, as shown in 5(b), while trips finish in a higher rate, as shown in 5(c). A clearer depiction of production evolution over time is given in 5(e), where higher network capacity compared to FTC is demonstrated in all MP cases. Comparing the MP cases with different number of controlled nodes, we can see that differences between them are disproportionately small compared to their implementation costs, that rises with the number of controlled intersections.

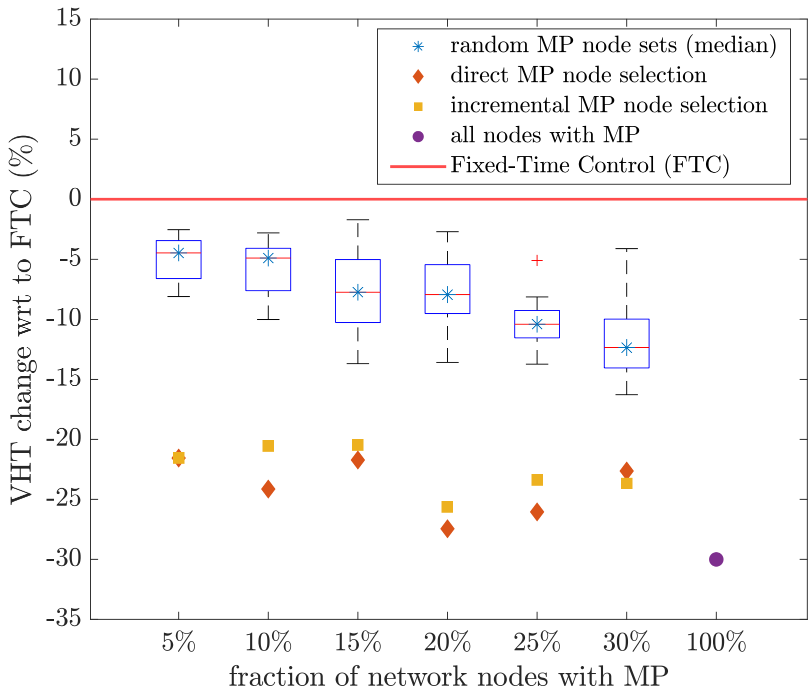


Figure 2: Comparison of travel time improvement with respect to the fixed-time control (FTC) case of tested cases. Boxplots depict performace of randomly selected node sets. Diamonds and squares correspond to the proposed selection strategy. Circle shows performance of case with all nodes controlled.

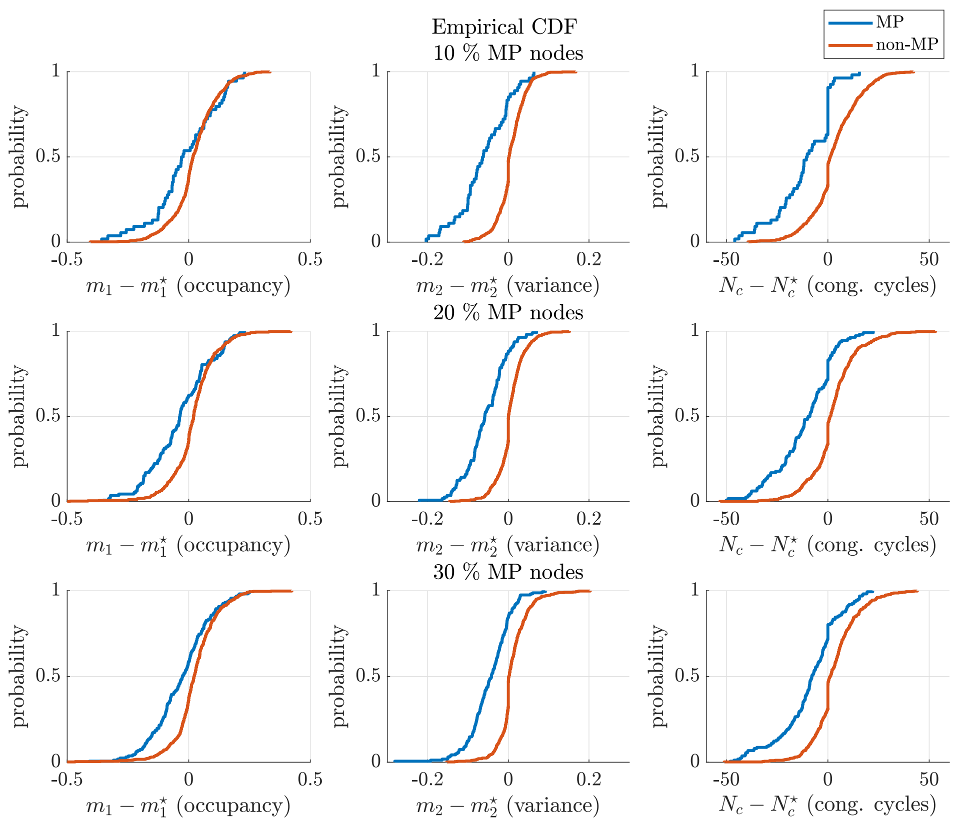
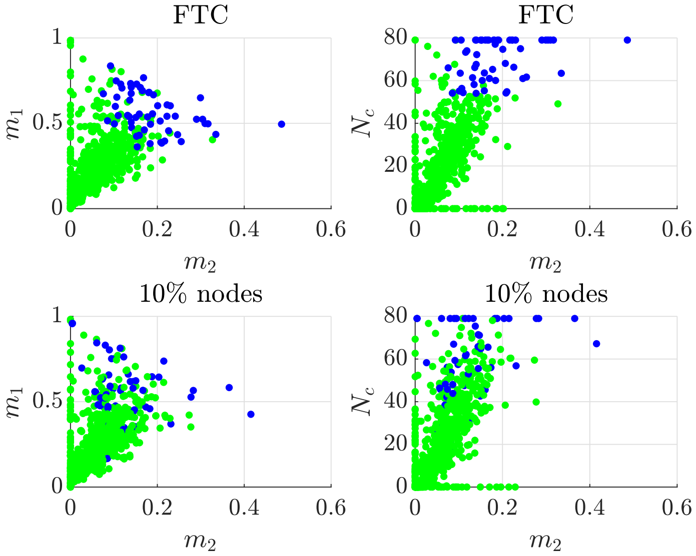
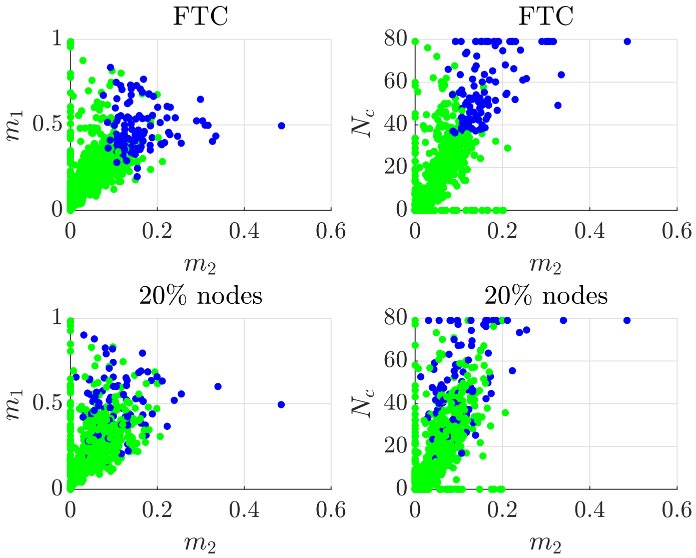


Figure 3: Empirical CDF for the observed difference in selection metrics m_1, m_2 and N_c after MP application, with respect to their values in FTC case, separately for MP (blue) and non-MP (red) nodes. The * indicates FTC case.



(a)



(b)

Figure 4: Changes in measures m_1, m_2 and N_c, reflecting average node occupancy, queue variance and high congestion time, respectively, for MP (blue) and non-Mp (green) nodes, before and after MP implementation. FTC represents the situation before, which is used for the selection of nodes: (a) case of 10% nodes; (b) case of 20% nodes.

Table 2: Mean values of differences of node selection metrics with respect to FTC for different MP node sets (cases), calculated separately for nodes with and without MP controller.

Case	Nodes	$m_1 - m_1^\star$	$m_2 - m_2^\star$	$N_c - N_c^\star$
10 %	MP	-0.0146	-0.0604	-11.41
	non-MP	0.0239	0.0061	2.9619
20 %	MP	-0.0364	-0.0569	-11.47
	non-MP	0.0187	0.0047	2.2719
30%	MP	-0.0296	-0.0460	-8.8463
	non-MP	0.0250	0.0104	3.2165

4. CONCLUSIONS

In this work, decentralized signal control based on the existing Max-Pressure controller is presented and applied in a large-scale network instance using a dynamic queue-based traffic simulation model. We focus on investigating how system performance of MP framework is affected by changing the number of controlled intersections, in an effort to increase the method's applicability by decreasing the cost related to its infrastructure requirements. We propose and evaluate the effectiveness of a classification method for critical node identification, based on information of currently experienced congestion, mean and variance of adjacent queues, with the aim of identifying a MP node layout that would lead to high performance with lower cost, which translates in achieving maximum travel time improvement with minimum number of controlled nodes.

The results unravel several interesting findings. Firstly, significant improvement in travel time and network serving capacity is achieved in all MP scenarios. The proposed critical node selection method is shown effective in generating MP node sets that not only perform significantly better than randomly selected sets, but also achieve performance close to the one of the global MP implementation. Moreover, MP leads to increasing the network serving capacity, in terms of travel production, even with few controlled nodes. In the proposed case study, it was found that more than 90% of the performance improvement by global MP application can be achieved by controlling only 20% of networks nodes, therefore with a cost reduced by 80%. Secondly, it is shown that MP is particularly efficient in reducing queue variance and congestion levels in the proximity of the controlled node, but it can also have a wider network effect in other nodes, not necessarily in the proximity of the controlled ones. In other words, the ability of MP controller in reducing traffic heterogeneity in congested networks is demonstrated. This can motivate research in efficient ways of combining decentralized MP control with centralized control systems, such as MFD-based perimeter control, that can highly benefit from this property. Future work should include the combination of MP node selection with perimeter control. A recent study by (Keyvan-Ekbatani, Gao, Gayah, & Knoop, 2019) combined an adaptive local controller in all nodes together with perimeter control for a single region and showed important improvements. Investigating how a novel critical node selection method coupled with perimeter control for multi-region systems could improve traffic performance should be a research priority.

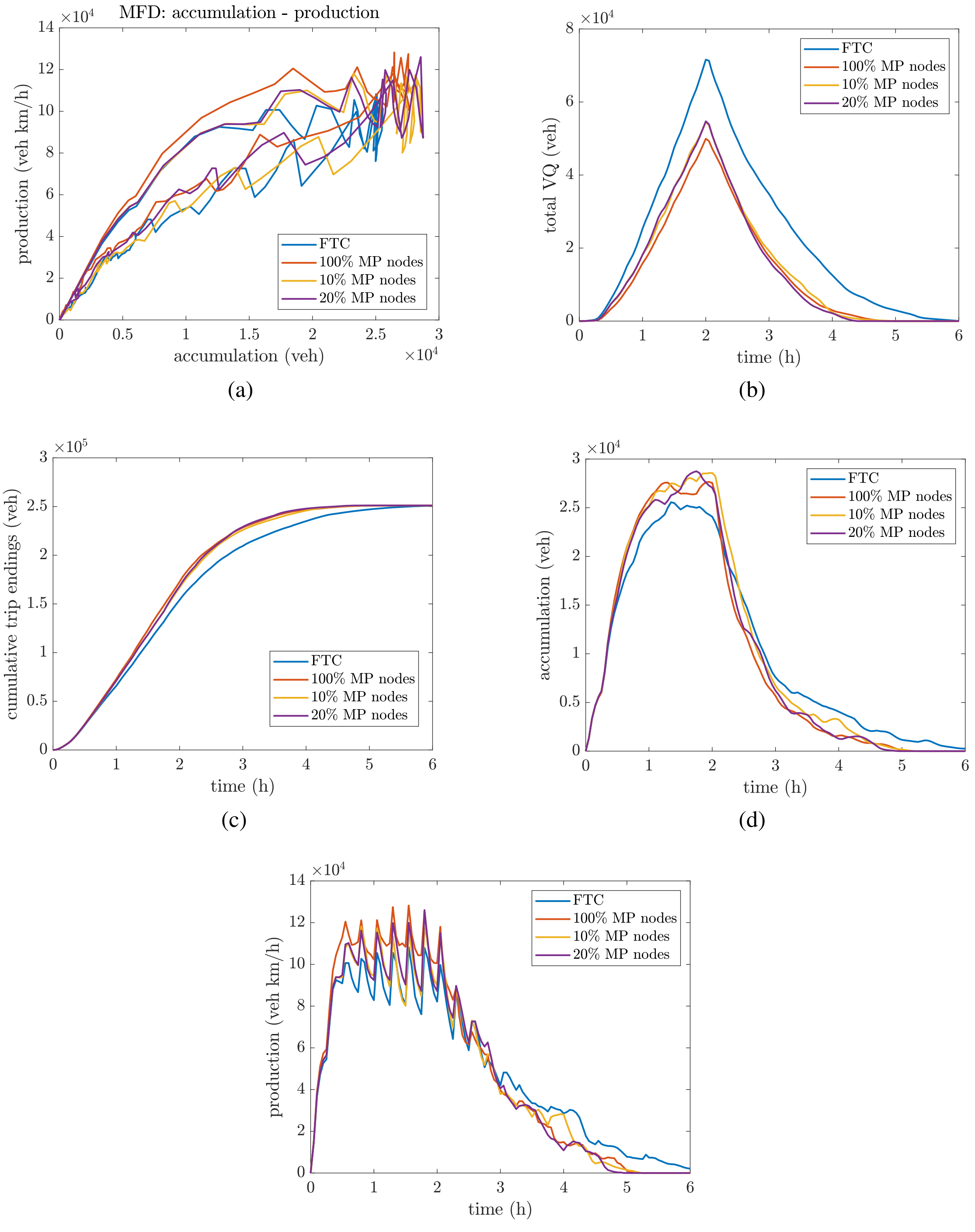


Figure 5: Comparison of simulation results of the three best performing MP control scenarios, with 10%, 20% and '100%' MP nodes, compared to the fixed-time control case 'FTC'.

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