Supplementary Material

Optimal and Objective Placement of Sensors in Water Distribution Systems Using Information Theory

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A Numerical Example for Calculation of VOI

A numerical example is provided here to illustrate the calculation of $VOI_i(j)$. Assume that, a decision maker placed a sensor at node i and would like to determine the detection states of node j which is without a sensor. Two detection states are determined for the entire WDS, i.e. s_1 and s_2 for detection of a contamination before and after 60 minutes, respectively. Also, two sets of data are available for calculation. The first data set is the records of 2,000 contamination injection scenarios which include the time that the contamination is detectable at every node in WDS. This set is interpreted as prior belief dataset which could be either the real data from pilot tests or the result from simulation of random scenarios. Here, we used the results of simulation of random scenarios. The second data set is the simulation results of 500 possible scenarios (random scenarios) which will be used for updating prior belief (evidence dataset). The number of scenarios in which the contamination is detectable in the detection states at node i and j are provided in table S1. For each detection state at node j, there would be message m, from the sensor at node i and an action a from the WDS's utility. Hence, a cost $C(s,a)$ matrix can be defined considering the consequences of the time lag between contamination reaching node j and released warning by utility manager based on the received message from sensor at node i (Table S1).

Table S1. Number of scenarios detectable in detection states at node i and j for both sets of data and their associated consequences.

Detection state of node j	Number of scenarios in "prior belief" dataset	Number of scenarios in "evidence" dataset, in which contamination is detectable at node i		Associated consequences of action a based on received message from node i	
		m_1	m_2	a_1	a_2
s_1	247	62	3	0	-500
s_2	1753	50	385	-500	0

The second column in Table S1, shows the number of scenarios in prior belief dataset in which contamination is detectable at node j in detection states, s_1 and s_2, respectively. The third and fourth columns, shows the number of scenarios in evidence dataset in which the contamination is detectable at node j in detection state s_k, while the sensor at node i has also detected the contamination in $m_{k'}$ minutes from injection. For example in column 3, 62 refers to the 62 scenarios in evidence dataset that are detected before 60 minutes from injection by the sensor at node i, while, the contamination in the same scenarios is also detectable before 60 minutes at node j. The fifth and sixth columns also show the cost of performing action $a_{k''}$, (releasing no consumption warning for node j) while the detection state at node j is s_k. It is obvious that if contamination is detectable at node j, for example, in less than 60 minutes from its injection (detection state s_1), and the WDS's utility releases warning to consumers of node j in less than 60 minutes (action a_1) from injection of contamination, there would be no damage to consumers' health. If the WDS's utility perform action a_2, which means release warning for consumers of node j, any time after 60 minutes, while the contamination was detectable at node j in the first 60 minutes from its injection (s_1), consumers would be exposed to contamination and hence a fraction of consumers would be affected. A value of -500 is assigned to such action in the cost matrix to account for affected population.

To calculate the updated belief, $P(s|m)$ in eq.1, one have to calculate prior probability of having detection states at node j, $P(s)$, from prior belief dataset, $P(m|s)$ and $P(m)$ from evidence dataset as follows:

$$P(s) = \begin{bmatrix} (62+50)/500 \\ (3+385)/500 \end{bmatrix} = \begin{bmatrix} 0.1235 \\ 0.8765 \end{bmatrix} \tag{s1}$$

$$P(m|s) = \begin{bmatrix} 62/(62+3) & 3/(62+3) \\ 50/(50+385) & 385/(50+385) \end{bmatrix} = \begin{bmatrix} 0.9538 & 0.0462 \\ 0.1149 & 0.8851 \end{bmatrix} \tag{s2}$$

$$P(m) = \begin{bmatrix} 247/2000 \\ 1753/2000 \end{bmatrix} = \begin{bmatrix} 0.224 \\ 0.776 \end{bmatrix} \tag{s3}$$

Now, the updated belief from eq.1 can be easily calculated as follows:

$$P(s|m) = \begin{bmatrix} 0.9538 \times 0.1235/0.224 & 0.0462 \times 0.1235/0.776 \\ 0.1149 \times 0.8765/0.225 & 0.8851 \times 0.8765/0.776 \end{bmatrix} = \begin{bmatrix} 0.5259 & 0.0073 \\ 0.4498 & 0.9997 \end{bmatrix} \tag{s4}$$

Hence, u_m and u_s (eqs.2) can be calculated as follows:

$$u_m = \begin{bmatrix} 0 \times 0.5259 - 500 \times 0.4498 & -500 \times 0.5259 + 0 \times 0.4498 \\ 0 \times 0.0073 - 500 \times 0.9997 & -500 \times 0.0073 + 0 \times 0.9997 \end{bmatrix} = \begin{bmatrix} -224.88 & -262.95 \\ -499.84 & -3.67 \end{bmatrix} \tag{s5}$$

$$u_s = \begin{bmatrix} 0 \times 0.1235 - 500 \times 0.8765 \\ -500 \times 0.1235 + 0 \times 0.8765 \end{bmatrix} = \begin{bmatrix} -438.25 \\ -61.75 \end{bmatrix} \tag{s6}$$

So, $VOI_i(j)$ from eq.3 would be:

$$\begin{aligned} VOI_i(j) = 0.224 \times (\max\{-224.88, -262.95\} - \max\{-438.25, -61.75\}) + 0.776 \\ \times (\max\{-499.84, -3.67\} - \max\{-438.25, -61.75\}) = -36.54 + 45.068 \\ = 8.5264 \end{aligned} \tag{s7}$$

Evaluating Performance of Proposed Model against TEVA-SPOT

Threat Ensemble Vulnerability Assessment-Sensor Placement Optimization Tool or briefly TEVA-SPOT, is a sensor placement optimization model which was under development from the early 2000s (Berry et al. 2008) by US Environmental Protection Agency (EPA), Sandia National Laboratories, Argonne National Laboratory, and the University of Cincinnati (Janke et al. 2017).

Its latest major release was in 2008 (Berry et al. 2008). Although, minor upgrades were released since then and the latest minor release of the model dates back to 2011 (Berry et al. 2012). Also, the latest release of the Graphical User Interface (GUI) of the model was in September 2017 (Janke et al. 2017), which is TEVA-SPOT GUI version 2.3.2. The development of this model is funded by US Environmental Protection Agency (EPA) as conformance to Presidential Directives for addressing critical needs for homeland security following the terrorist attacks of September 11, 2001. Like other models, it consists of three main modules, i.e. simulation module, impact assessment module and optimization module. TEVA-SPOT (TS model) is the most well-known and proven model among the researchers.

In previous sections of the paper, we have compared the results of Value of Information and Transinformation Entropy optimization model (VT model) for the case study of Lamerd WDS with two previous studies on the same case study (i.e. Bazargan-Lari, 2014; Naserizade et al. 2018). The results show that the efficiency of VT model has provided the capability of enhancing the decision space, and hence, more objective approach to sensor placement optimization. Therefore, the resulted CWS designs are more safe than those of the previous studies from time to detection (Td), affected population (Pa) and probability of detecting contamination (Pd) viewpoint. Also, a comparison between VT and TS models' performances for design of CWS in Lamerd WDS is briefly provided in the paper. In this section, more detailed report regarding this comparison is provided. This comparison is based on memory requirements and runtime (computational efficiency) and also results accuracy.

Table S2 shows some basic features of the models. The green cells indicate the advantage of the corresponding model compared to the other model. The comparisons are based on the discussions provided in Murray et al. (2010) and Janke et al. (2017) and the experience of the authors which will be discussed later. In simulation modules, both models use the same version of EPANET (Rossman 2000; EPANET v2). Also, its latest extension (EPANET-MSX) is included in TS model for simulation of multi-species contamination events, while, this extension is not included in VT model currently and multi-species contamination events are not considered in this study. According to TS model's Users' Manual (Janke et al. 2017), the memory requirements of this model is relatively high as shown in the later part of this report, while, memory requirements of VT model is significantly low compared to TS model. Also, the optimization module of TS model uses single-objective optimization algorithm, however, according to Janke et al. (2017), the model offers constrained optimization to achieve designs considering multi-criteria. Also, the designer should specify the number of sensors to be placed in WDS. Hence, the designer should perform multiple optimizations in an iterative manner to find the most suitable number of sensors which satisfies different criteria. On the other hand, VT model uses a multi-objective optimization algorithm (NSGA-II), and hence, the designer does not have to perform multiple optimizations nor specify the exact number of sensors. Instead, the designer could specify an upper bound on number of sensors to be placed in WDS and trade multiple criteria against each other after a single-time execution of optimization module. Also, based on discussion that provided in introduction and methodology section, VT model optimizes the whole probability distribution functions (pdfs) of both Td and Pa by means of optimizing VOI of selected nodes for placement of sensors. Also, it uses TE to maximize Pd, however, TS model optimizes only a signature of those pdfs at a time.

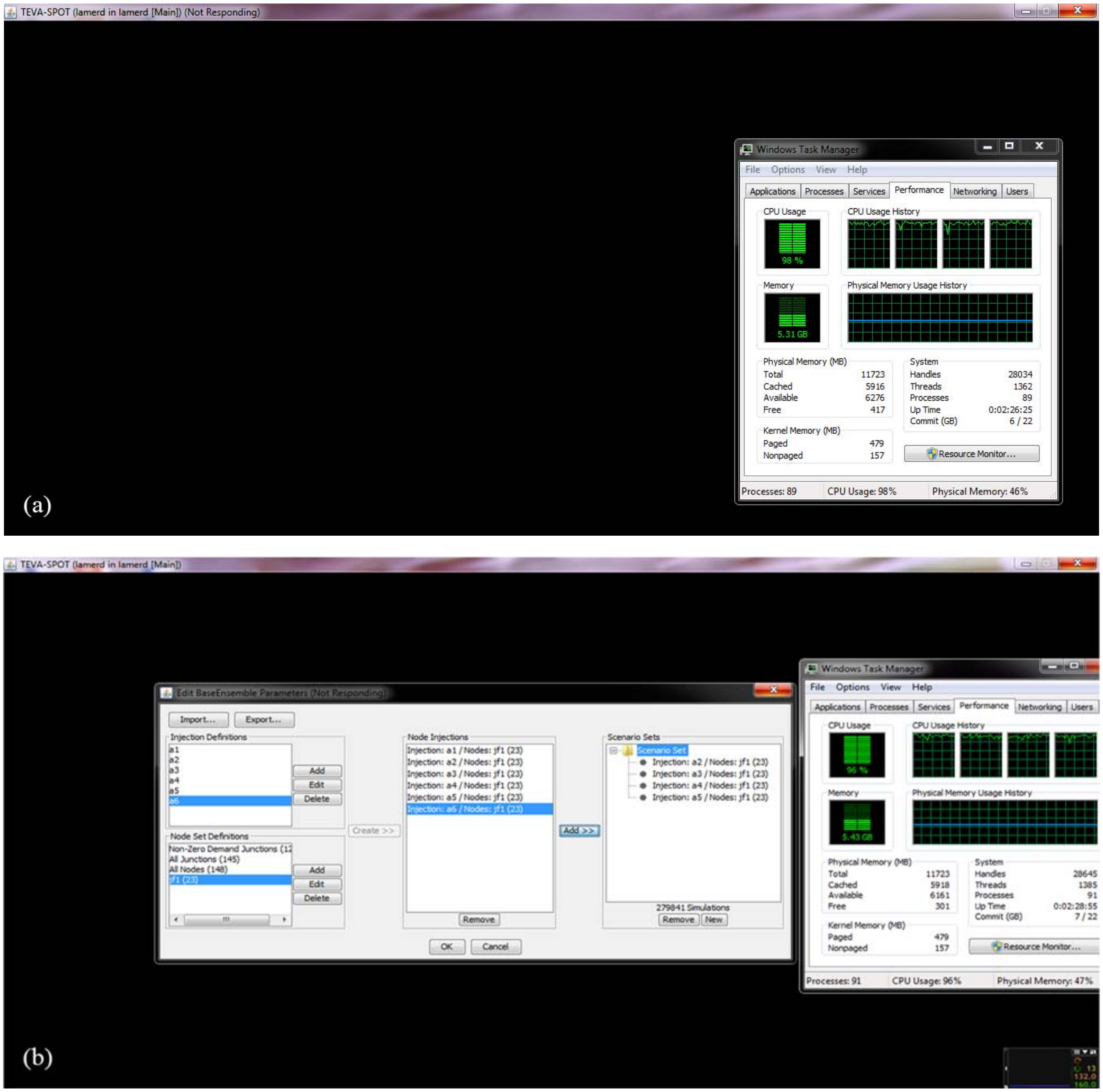
Table S2. Comparison between the basic features of TS and VT models. The green color indicates the advantage of the corresponding model compared to the other model.

Feature	*TS model*	*VT model*
Memory requirements	High	**Low**
Multi-species simulation	**Yes**	No*
Flexible number of sensors	No	**Yes**
Multi-objective optimization	No	**Yes**
Constrained optimization	**Yes**	**Yes**
Type of optimization; i.e. consideration of pdfs in optimization module	Mean of pdfs and Robust optimization (there is no option to perform both simultaneously)	**Whole pdfs (the discussion provided in introduction and methodology sections).**

* Multi-species simulation of multiple toxin or biological species has not considered in this study, however, it can be included in the simulation module of VT model with little modifications.

The following is the report of our comparison. Beforehand, it is worth mentioning that, as we have expected, VT model has outperformed TS model, both from computational efficiency and accuracy viewpoint. Please note that, Lamerd WDS is very smaller than WDS of large cities. So, we expect VT model to be significantly faster and more accurate than TS model for very large WDSs.

Both models were executed on a desktop PC (CPU: Intel® Core™ i7-4500U; RAM: 12GB DDR3). At the first instance, we decided to simulate a large number of scenarios (more than 270000 scenarios). The simulation module of VT model, had well performed the simulations and the results were ready to use in its other modules, however, it was not the case for TS model. When we defined the simulation scenarios, the PC became unresponsive and after a few moments, its operating system crashed. However, we managed to capture a few screenshots before the crash of the operating system (Figs. S1).



Figs. S1. Two screenshots from the desktop PC after defining over 270000 simulation scenarios. The Microsoft Windows ® Task Manager shows significant load on the CPU of the PC.

According to TS model's Users' Manual (Janke et al. 2017), when the number of simulation scenarios and/or size of WDS are large, the CWS design by TS model could not be performed on a typical computer, instead Workstations with sufficient resources should be used (Janke et al. 2017). Even, the same problem occurred for 100000 and 75000 number of simulation scenarios.

After some iterations, we have managed to find a suitable number of scenarios for TS model (about 12000 scenarios) and used those simulations scenarios for VT model, too, to make fair comparison. To compare the two models and since TS uses a single-objective optimization module and requires the user to specify the number of sensors to be placed in WDS, the 3rd objective of VT models' optimization module (i.e. minimization of number of sensors) is removed and the module constrained to place a fixed number of sensors into WDS. Also, the optimization modules of both models were constrained to provide at least 80% probability of detection of contamination events (i.e. $Pd \geq 0.8$). To fairly compare the models, the model parameters of EPANET are specified for both models as same as each other. Hence, the results of the simulation modules would be the same. Also, Arsenic is considered as the contamination to be injected in WDS. Furthermore, four injection mass with four different injection durations beginning at 5 AM are considered for generation of simulation scenarios. Also, 26 nodes (23 hydrants, 2 reservoirs and the tank in WDS) are considered for the location of injections. Single-node injection and simultaneous injection from two and three nodes are considered as contamination injection scenarios. Therefore, the number of simulation scenarios is four times the summation of combination of 1, 2 and 3 nodes from 26 nodes which result in 11804 unique injection scenarios. Then, the contamination injection scenarios were simulated by both models. The characteristics of the contamination scenarios and the parameters of the simulation modules are provided in Table S3.

Table S3. Characteristics of scenarios and parameters of simulation modules.

Parameter	Values
Time of injection	0500AM
Mass of injection	277 mg/sec, 352 mg/sec, 410 mg/sec, and 425 mg/sec
Duration of injection	78 min, 62 min, 46 min, and 76 min
Locations of injection	26 nodes: 23 hydrants, 2 reservoirs and a tank
Number of injections	Simultaneously from 1, 2 and 3 points
Total number of scenarios	$4 \times \left(\binom{26}{1} + \binom{26}{2} + \binom{26}{3}\right) = 11804$ scenarios
Simulation duration	2 days
Quality, hydraulic and Reporting time-step	1 min

Also, the optimization modules of both models were configured for optimal location design of 3, 4, 5, 6, 7, 8 and 9 sensors. To evaluate the robustness and accuracy of the solutions of VT model against TS model, two objectives were defined for the optimization module of TS model; i.e. minimization of the Value-at-Risk (VaR) of time to detection (Td_{VaR}) for robustness and minimization of average of time to detection (Td_{ave}). VaR of a pdf is the point in pdf where cumulative probability of the pdf exceeds a certain level. Interested readers are referred to Sarykalin et al. (2008) for more information.

The optimization module of TS model is single-objective, hence, it should be executed for every objective separately, providing a single solution for each objective. Hence, for each number of sensors to be placed in the WDS, there would be two solutions from the TS model, one for Td_{ave} and the other for Td_{VaR} which are denoted by TSM and TSV, respectively. On the other hand, the multi-objective optimization module of VT model was executed only once for each number of sensors to be placed in the WDS and will provide more than one solution (a pareto front) which are denoted by VT followed by a number. Then, the results were compared considering the following four criteria: 1. minimum time to detection (Td_{min}), 2. maximum time to detection

(Td_{max}), and, 3. average time to detection (Td_{ave}), and, 4. probability of detection in the first 60 minutes from the injection (Pd_{60}). The mean runtime of both models' modules are provided in Table S4.

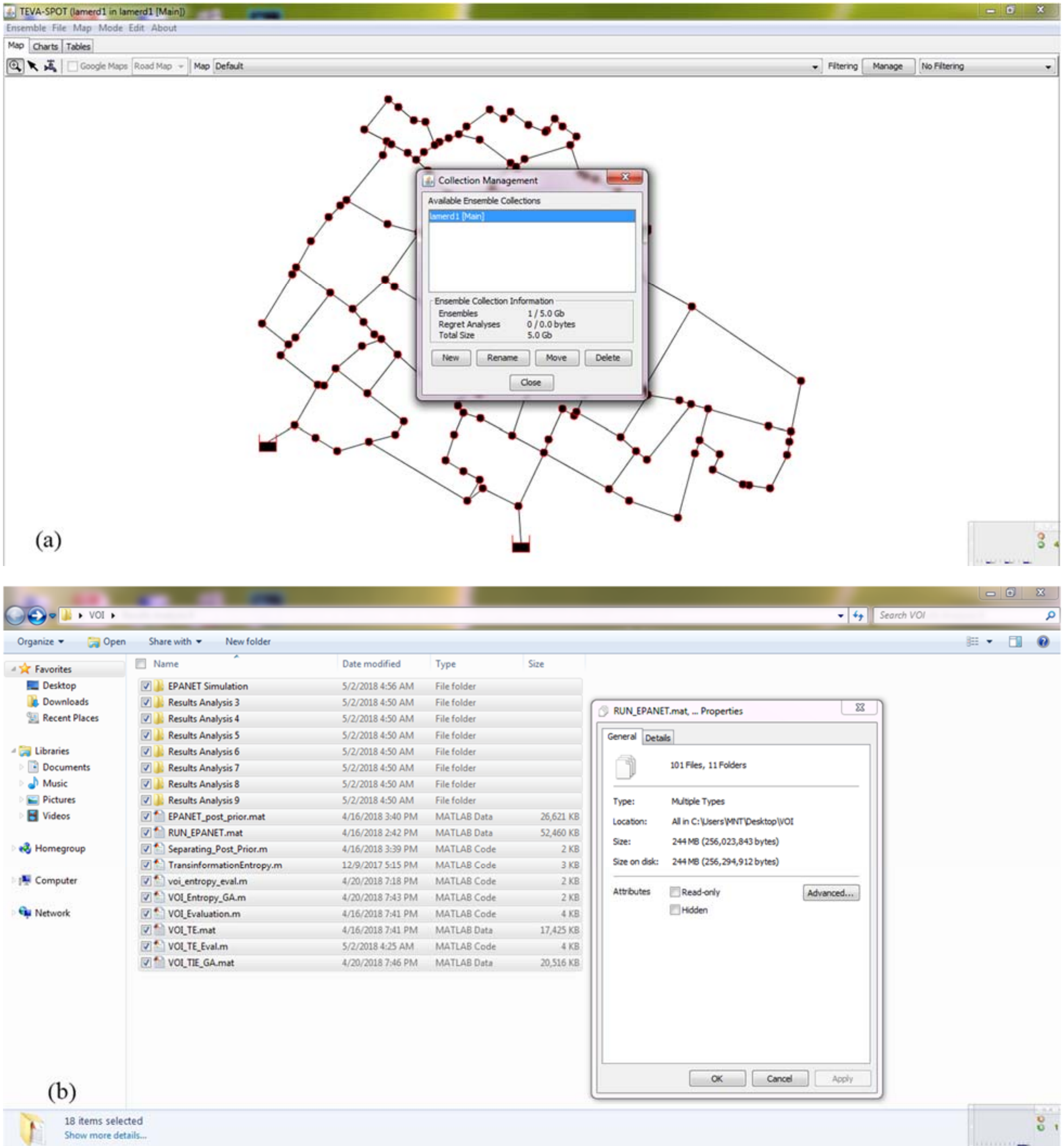
Table S4. The mean runtime of TS and VT models' modules.

TS Model		VT Model	
Module	Run-time (sec)	Module	Run-time (sec)
Simulation	2356	Simulation	2894
Health Impact Assessment	168	VOI+TE	37
Optimization*	297	Optimization*	107

* The values are the mean run-time for the design of the seven sets of sensors.

The table shows that, the simulation module of VT model is 23% slower than that of TS model, however, the VOI+TE and optimization modules of VT model are 350% and 177% faster than those of TS model, respectively.

To compare the memory requirements of the two models, the size of data which are generated by the models and are essential for their modules to work properly are compared. Fig. S2 (a) shows an screenshot from Collection Management feature of TS model, which indicates that TS model consumed 5 Giga Bytes of the disk space (5 Giga Bytes is equal to 5120 Mega Bytes). Fig. S2 (b) shows that all the scripts and data of VT model only consumed 244 Mega Bytes. Please note that when we execute the optimization modules of both models, the modules would transfer all of their respective data to PC's RAM and use them as inputs. In other words, the disk space and RAM usage of VT model are 1/20 those of TS model.



Figs. S2. (a) An screenshot from Ensemble Management of TS model, which shows the model occupied 5 Giga Byes (5120 Mega Bytes) of disk space, while, (b) VT model only occupied 244 Mega Bytes of the PC's disk space.

As mentioned earlier, we have identified four criteria for comparing accuracy and robustness of VT model against TS model; i.e. 1. minimum time to detection (Td_{min}), 2. maximum time to detection (Td_{max}), and, 3. average time to detection (Td_{ave}), and, 4. probability of detection in the first 60 minutes from the injection (Pd_{60}). In TS model's Users' Manual (Janke et al. 2017), it is recommended that the designers perform multiple optimizations with different objectives and then trade them off against each other to find the best CWS design which satisfies multiple criteria of interest. Here, we have adopted the same approach for comparing TS and VT models' designs by using a well-known multi-criteria decision making method named Technique for Order Preference by Similarity to Ideal Solution (TOPSIS; the interested readers are referred to Yoon and Hwang, (1981)). Although, in some cases, superiority of a certain solution is obvious, we use TOPSIS for ranking of the solutions for all cases. The results are provided in Table S5 including the labels of the selected nodes for placement of sensors and other parameters such as VOI, TE and probability of detection under 2 minutes from the injection (Pd_2) are provided for further comparison.

Table S5. The results of the TS and VT models for design of CWS with 3, 4, 5, 6, 7, 8 and 9 sensors in Lamerd WDS.

Set	Name	Selected Nodes	Objective(s)	VOI	TE	Td_{min} (min)	Td_{ave} (min)	Td_{max} (min)	Pd_{60}	Pd_2	TOPSIS Ranking
3 Sensors	TSM	{28,31,44}	Td_ave	16.77397	0.116832	9	63.75493	344	0.542712	0	13
	TSV	{28,40,61}	Td_VaR	11.10297	0.156512	3	83.81239	267	0.306441	0	8
	VT1	{18,31,64}	VOI & TE	25.48452	0.122934	1	65.54063	292	0.542712	0.110508	7
	VT2	{18,31,63}	VOI & TE	24.64656	0.119514	1	66.71381	265	0.542712	0.110508	5
	VT3	{18,31,65}	VOI & TE	24.64656	0.119514	1	62.2566	247	0.542712	0.110508	3
	VT4	**{18,31,66}**	**VOI & TE**	**22.56917**	**0.11754**	**1**	**49.8007**	**159**	**0.542712**	**0.212542**	**1**
	VT5	{19,87,89}	VOI & TE	22.44865	0.085355	1	63.25495	221	0.392542	0.110508	4
	VT6	{19,87,90}	VOI & TE	21.38294	0.064692	1	64.53241	221	0.306441	0.110508	6
	VT7	{19,31,64}	VOI & TE	19.72907	0.062808	10	67.95901	292	0.471186	0	14
	VT8	{19,31,65}	VOI & TE	18.89111	0.055969	10	64.73605	247	0.471186	0	12
	VT9	{19,31,66}	VOI & TE	16.81372	0.05202	1	52.25952	159	0.471186	0.110508	2
	VT10	{19,31,67}	VOI & TE	15.45981	0.04363	10	55.03707	136	0.471186	0	9
	VT11	{19,31,76}	VOI & TE	14.44758	0.038036	10	58.80829	135	0.392542	0	10
	VT12	{19,31,78}	VOI & TE	14.10689	0.037917	10	62.14184	165	0.392542	0	11
4 Sensors	TSM	{28,31,44,124}	Td_ave	18.24201	0.224353	3	49.10105	192	0.607458	0	3
	TSV	{28,31,44,124}	Td_VaR	18.24201	0.224353	3	49.10105	192	0.607458	0	4
	VT1	{18,22,57,66}	VOI & TE	30.71849	0.752208	1	55.2399	159	0.471186	0.212542	2
	VT2	**{11,15,57,67}**	**VOI & TE**	**30.57802**	**0.711998**	**2**	**47.61755**	**155**	**0.607458**	**0.110508**	**1**
	VT3	{11,18,57,68}	VOI & TE	30.3124	0.528481	1	57.09333	222	0.542712	0.212542	5
	VT4	{11,15,56,68}	VOI & TE	30.02987	0.523254	2	52.6665	220	0.542712	0.110508	7
	VT5	{11,15,57,71}	VOI & TE	29.96395	0.38461	2	57.2738	222	0.607458	0.110508	8
	VT6	{55,89,99,106}	VOI & TE	29.74604	0.38403	17	62.78485	208	0.471186	0	21
	VT7	{56,89,99,106}	VOI & TE	29.74604	0.38403	17	65.70085	220	0.471186	0	22
	VT8	{56,89,100,106}	VOI & TE	29.74604	0.38403	10	57.07182	220	0.542712	0	15
	VT9	{15,33,54,72}	VOI & TE	29.57123	0.314161	10	66.93583	214	0.471186	0	17
	VT10	{20,31,73,93}	VOI & TE	29.31856	0.289813	10	62.11038	267	0.607458	0	16
	VT11	{19,27,43,66}	VOI & TE	29.20461	0.272117	1	68.32313	252	0.471186	0.110508	13

	VT12	{15,33,45,72}	VOI & TE	28.90496	0.223586	1	62.48566	238	0.471186	0.110508	10
	VT13	{15,33,45,68}	VOI & TE	28.57965	0.217159	1	66.13566	238	0.392542	0.110508	14
	VT14	{15,31,45,73}	VOI & TE	28.17426	0.216015	1	47.427	238	0.607458	0.110508	6
	VT15	{15,31,45,75}	VOI & TE	27.84895	0.215119	1	49.64511	238	0.542712	0.110508	9
	VT16	{18,31,76,93}	VOI & TE	27.74108	0.130337	1	62.59843	267	0.542712	0.110508	12
	VT17	{15,31,46,76}	VOI & TE	24.36887	0.123996	10	59.75062	274	0.542712	0	18
	VT18	{15,31,46,78}	VOI & TE	24.02818	0.123877	10	61.53012	274	0.542712	0	19
	VT19	{15,39,45,71}	VOI & TE	22.32514	0.094929	1	69.97525	224	0.471186	0.110508	11
	VT20	{19,31,76,93}	VOI & TE	21.98563	0.067669	10	64.95794	267	0.471186	0	20
5 Sensors	TSM	{28,31,40,45,124}	Td_ave	21.98782	0.538974	1	41.30393	192	0.665763	0.110508	5
	TSV	{28,31,44,100,124}	Td_VaR	25.15394	0.481675	3	40.19056	179	0.717966	0	10
	VT1	{1,18,27,55,100}	VOI & TE	32.97153	0.77858	1	40.84188	208	0.764407	0.212542	6
	VT2	{1,18,22,55,100}	VOI & TE	32.7322	0.777733	1	42.8885	208	0.764407	0.212542	7
	VT3	{1,18,27,45,100}	VOI & TE	32.45831	0.70688	1	39.94704	238	0.764407	0.306441	8
	VT4	{1,18,27,100,115}	VOI & TE	32.15561	0.700669	1	42.78421	250	0.764407	0.212542	9
	VT5	**{1,18,55,100,124}**	**VOI & TE**	**29.89716**	**0.65432**	**1**	**39.02978**	**145**	**0.764407**	**0.212542**	**1**
	VT6	{1,18,45,100,124}	VOI & TE	29.53036	0.599084	1	36.91048	171	0.764407	0.306441	2
	VT7	{1,28,45,100,124}	VOI & TE	28.54408	0.483117	1	38.78212	171	0.764407	0.212542	3
	VT8	{1,18,35,87,124}	VOI & TE	26.768	0.411585	1	41.70506	192	0.764407	0.306441	4
6 Sensors	TSM	{15,28,31,40,45,124}	Td_ave	23.79646	1.604539	1	31.9749	192	0.764407	0.110508	12
	TSV	{18,28,31,44,100,124}	Td_VaR	27.40366	0.934921	1	32.94888	179	0.805424	0.110508	11
	VT1	{1,18,27,45,87,100}	VOI & TE	35.06979	1.288535	1	26.28882	128	0.805424	0.392542	2
	VT2	{1,18,22,45,87,100}	VOI & TE	34.83047	1.287688	1	27.95901	128	0.805424	0.392542	4
	VT3	{1,18,27,87,100,115}	VOI & TE	34.18355	1.171758	1	27.70684	128	0.805424	0.306441	3
	VT4	**{1,11,18,87,100,115}**	**VOI & TE**	**34.18355**	**1.171758**	**1**	**24.79165**	**128**	**0.805424**	**0.392542**	**1**
	VT5	{1,11,18,28,55,100}	VOI & TE	34.10453	1.104395	1	32.42444	208	0.841356	0.306441	13
	VT6	{1,18,27,55,100,124}	VOI & TE	33.71156	0.928516	1	35.4176	145	0.805424	0.212542	5
	VT7	{1,18,27,45,100,124}	VOI & TE	33.34476	0.873281	1	33.27915	171	0.805424	0.306441	7
	VT8	{1,18,22,45,100,124}	VOI & TE	33.10543	0.872433	1	34.84931	171	0.805424	0.306441	10
	VT9	{1,28,30,45,100,124}	VOI & TE	31.65157	0.830272	1	33.50954	171	0.805424	0.212542	8

	VT10	{1,18,35,45,100,124}	VOI & TE	30.53476	0.668333	1	33.7242	171	0.841356	0.306441	6
	VT11	{1,28,35,45,100,124}	VOI & TE	29.54848	0.552365	1	34.92695	171	0.841356	0.212542	9
7 Sensors	TSM	{11,15,28,31,40,45,124}	Td_ave	30.85925	1.859207	1	25.57259	192	0.841356	0.212542	12
	TSV	{1,15,28,31,45,59,100}	Td_VaR	33.46646	2.126152	1	27.40483	191	0.899322	0.212542	13
	VT1	**{1,18,28,30,45,87,100}**	**VOI & TE**	**35.54986**	**1.6227**	**1**	**23.07601**	**128**	**0.872542**	**0.392542**	**1**
	VT2	{1,18,28,30,31,55,100}	VOI & TE	35.09893	1.568615	1	28.61704	208	0.899322	0.212542	14
	VT3	{1,18,26,28,87,100,115}	VOI & TE	34.89492	1.544809	1	24.45821	128	0.841356	0.306441	3
	VT4	{1,18,28,30,87,100,115}	VOI & TE	34.66362	1.505923	1	24.2422	128	0.872542	0.306441	2
	VT5	{1,18,28,30,31,45,100}	VOI & TE	34.58571	1.499641	1	26.46572	238	0.899322	0.306441	15
	VT6	{18,28,30,31,47,87,100}	VOI & TE	34.51669	1.384422	1	29.45584	128	0.841356	0.212542	7
	VT7	{1,18,30,87,100,115,124}	VOI & TE	34.20664	1.330044	1	25.44552	145	0.841356	0.306441	4
	VT8	{1,18,28,30,55,100,124}	VOI & TE	34.19163	1.262681	1	29.22057	145	0.872542	0.212542	8
	VT9	{1,18,28,30,45,100,124}	VOI & TE	33.82483	1.207446	1	26.85911	171	0.872542	0.306441	10
	VT10	{1,18,26,35,87,100,124}	VOI & TE	32.05739	1.168561	1	27.00576	145	0.841356	0.306441	5
	VT11	{1,18,35,87,100,115,124}	VOI & TE	32.02934	1.116746	1	27.69377	145	0.872542	0.306441	6
	VT12	{1,18,28,35,64,100,124}	VOI & TE	31.84224	1.100618	1	29.91366	145	0.899322	0.212542	9
	VT13	{1,18,28,35,100,115,124}	VOI & TE	31.39324	0.998635	1	29.91422	182	0.899322	0.212542	11
8 Sensors	TSM	{11,15,28,30,31,40,45,124}	Td_ave	31.18343	2.196131	1	21.59754	192	0.872542	0.212542	7
	TSV	{1,15,28,31,45,59,100,109}	Td_VaR	34.34404	2.798189	1	25.97404	191	0.922034	0.212542	8
	VT1	**{1,18,28,30,31,54,87,100}**	**VOI & TE**	**36.47583**	**2.371481**	**1**	**22.98052**	**128**	**0.922034**	**0.306441**	**1**
	VT2	{1,18,28,30,31,47,87,100}	VOI & TE	36.31095	1.961793	1	23.70095	128	0.922034	0.306441	3
	VT3	{1,18,28,29,31,87,100,115}	VOI & TE	35.43734	1.932197	1	24.50129	128	0.922034	0.306441	4
	VT4	{1,14,18,28,31,44,87,100}	VOI & TE	35.2513	1.887083	1	24.37449	342	0.922034	0.306441	9
	VT5	{1,18,28,30,31,87,100,124}	VOI & TE	33.60202	1.830869	1	21.34715	145	0.922034	0.306441	2
	VT6	{1,18,28,35,87,100,115,124}	VOI & TE	33.21632	1.44256	1	24.23847	145	0.922034	0.306441	5
	VT7	{1,18,28,35,40,87,100,124}	VOI & TE	30.36928	1.39501	1	24.40986	152	0.922034	0.306441	6
9 Sensors	TSM	{11,15,28,30,31,40,45,87,124}	Td_ave	34.87522	2.793573	1	17.385	192	0.899322	0.306441	3
	TSV	{1,15,28,31,45,54,59,100,110}	Td_VaR	35.25736	3.605313	1	23.89879	191	0.941017	0.212542	4
	VT1	{1,11,18,28,31,35,45,66,87}	VOI & TE	38.93832	2.82791	1	21.77335	286	0.922034	0.542712	6
	VT2	{1,11,15,18,31,35,45,87,100}	VOI & TE	38.67842	2.47531	1	22.7441	286	0.922034	0.471186	7

	VT3	{1,11,18,28,31,35,45,87,100}	VOI & TE	38.668	2.19986	1	20.92077	286	0.941017	0.471186	5
	VT4	{1,8,18,28,30,31,35,45,87}	VOI & TE	38.57406	2.161198	1	22.75907	286	0.922034	0.471186	8
	VT5	{1,11,18,31,35,45,87,100,124}	VOI & TE	38.18134	2.024099	1	19.22225	145	0.922034	0.471186	2
	VT6	**{1,11,18,28,35,45,87,100,124}**	**VOI & TE**	**37.85354**	**1.833534**	**1**	**18.94578**	**145**	**0.941017**	**0.471186**	**1**

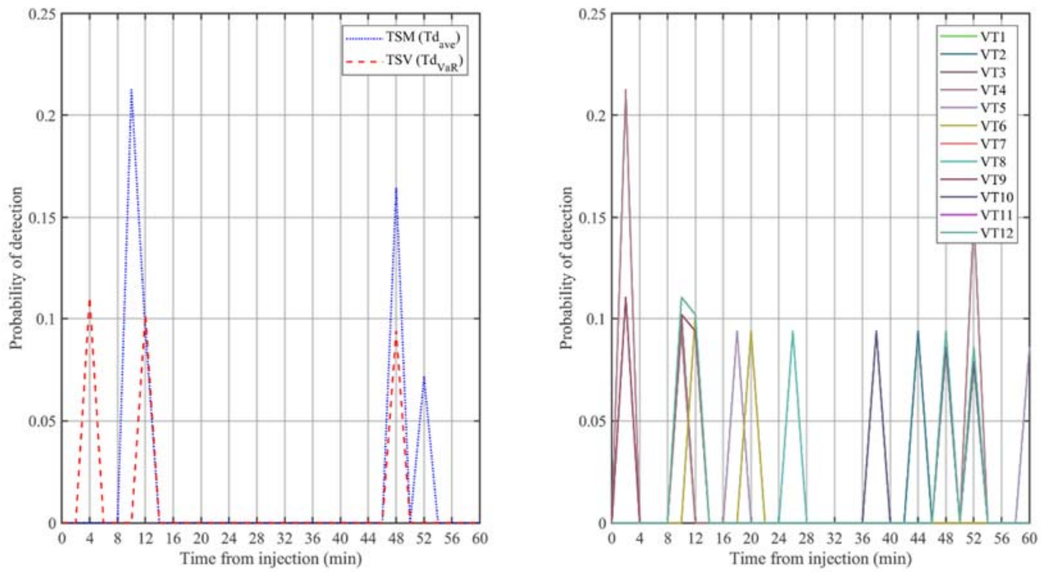


Fig. S3. Probability distribution of time to detection for CWS with 3 sensors designed by TS (left) and VT (right).

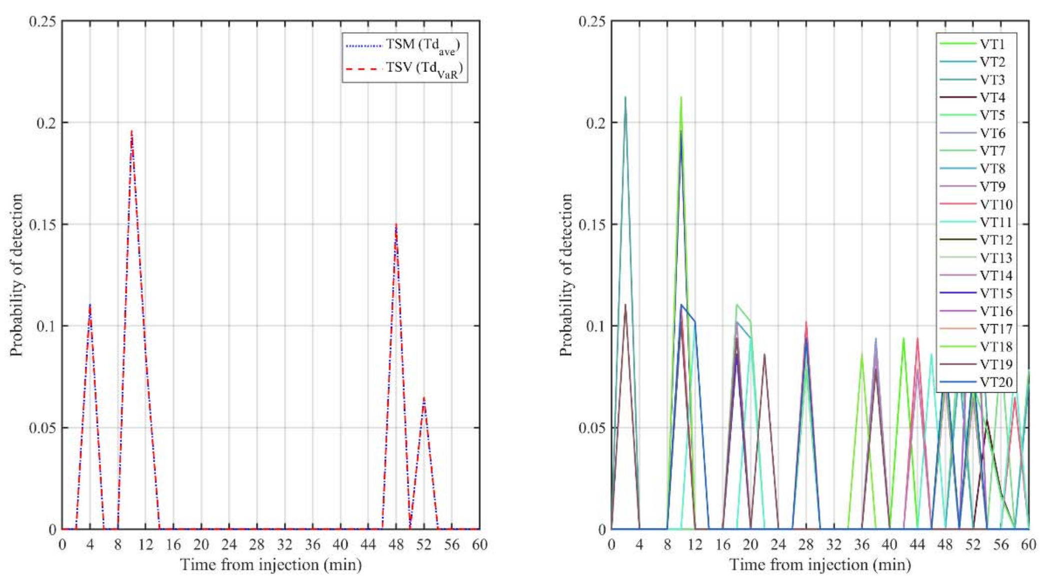


Fig. S4. Probability distribution of time to detection for CWS with 4 sensors designed by TS (left) and VT (right).

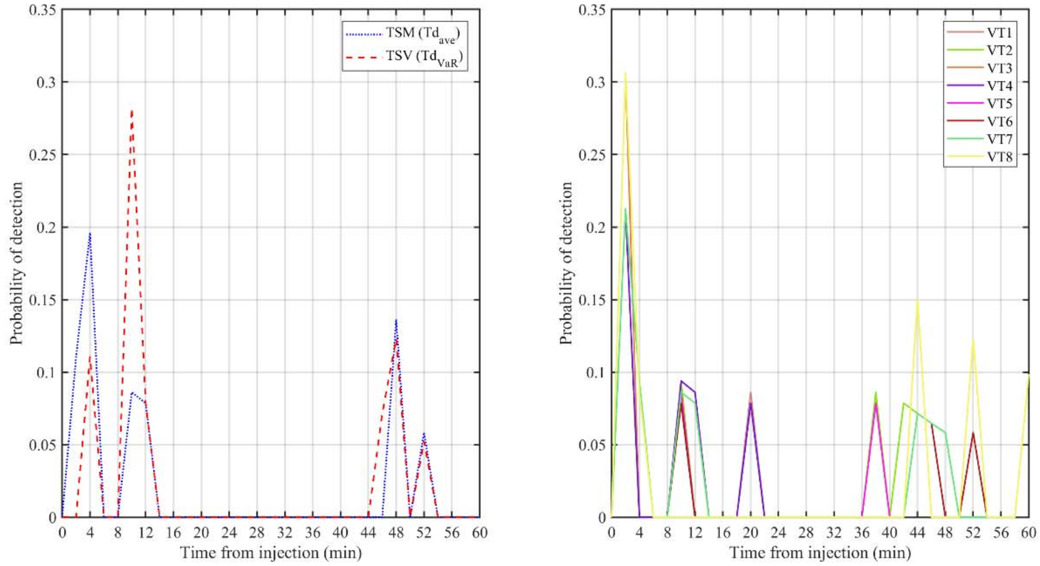


Fig. S5. Probability distribution of time to detection for CWS with 5 sensors designed by TS (left) and VT (right).

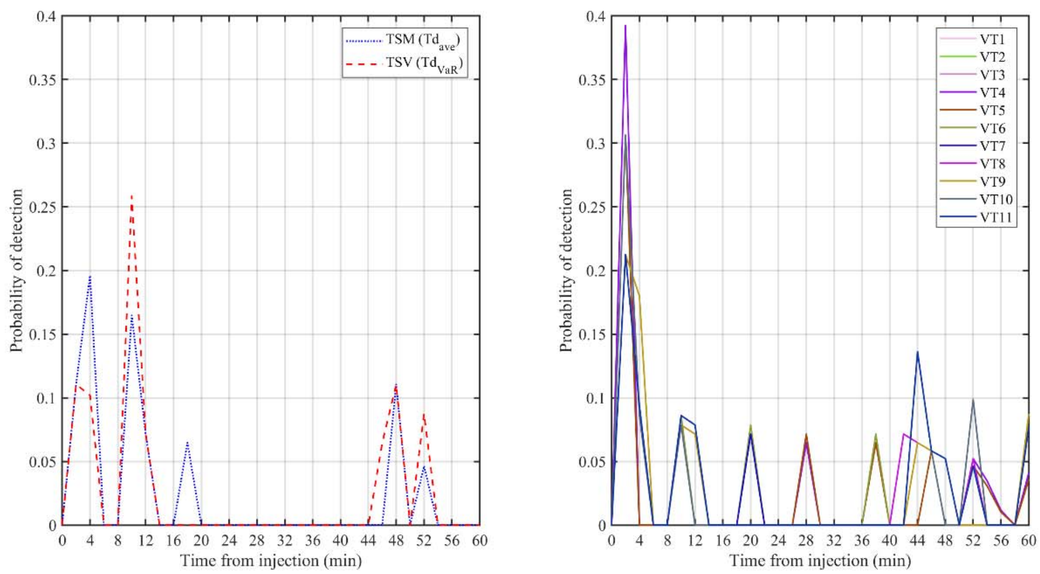


Fig. S6. Probability distribution of time to detection for CWS with 6 sensors designed by TS (left) and VT (right).

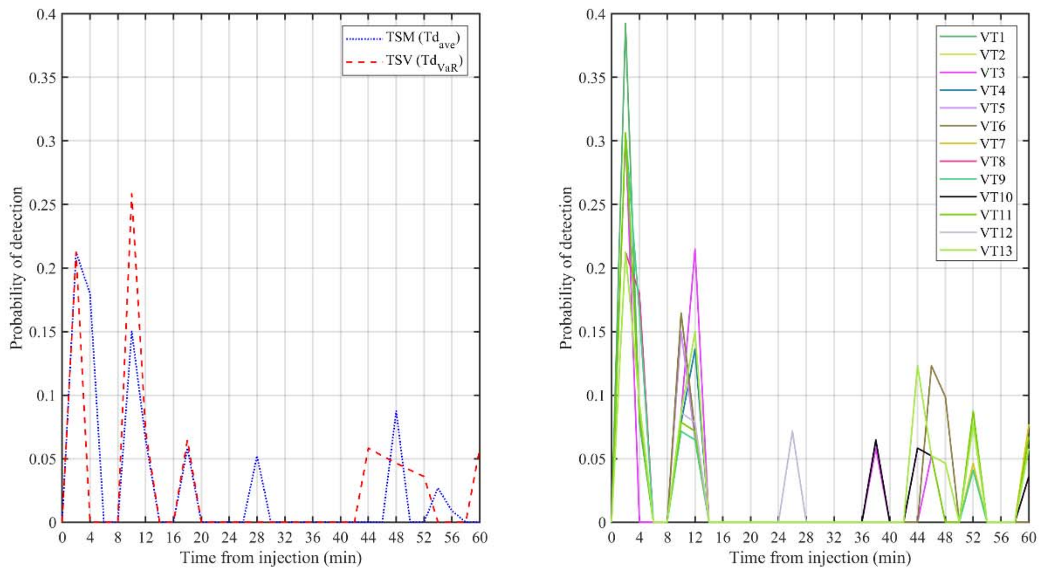


Fig. S7. Probability distribution of time to detection for CWS with 7 sensors designed by TS (left) and VT (right).

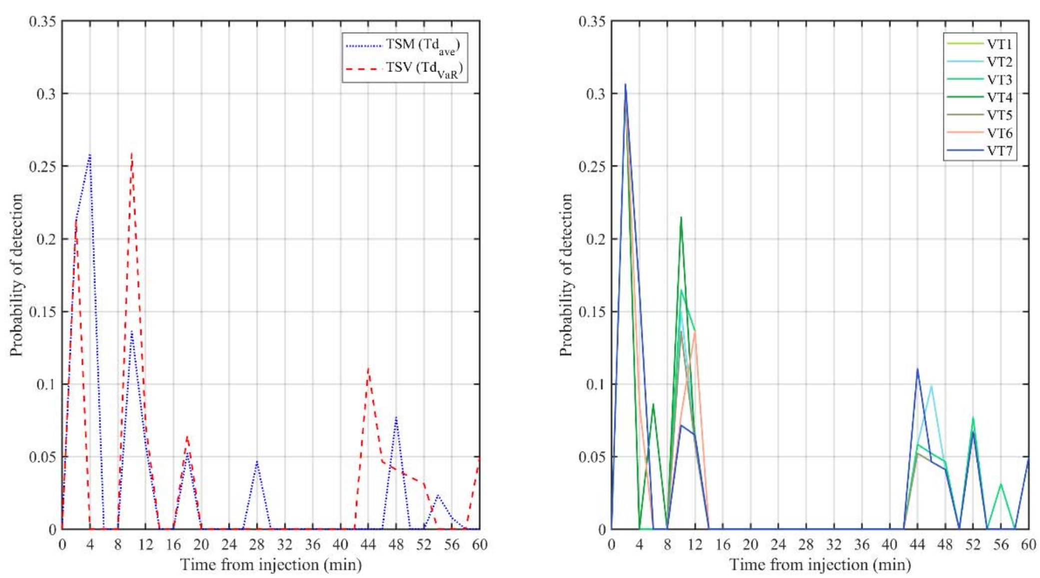


Fig. S8. Probability distribution of time to detection for CWS with 8 sensors designed by TS (left) and VT (right).

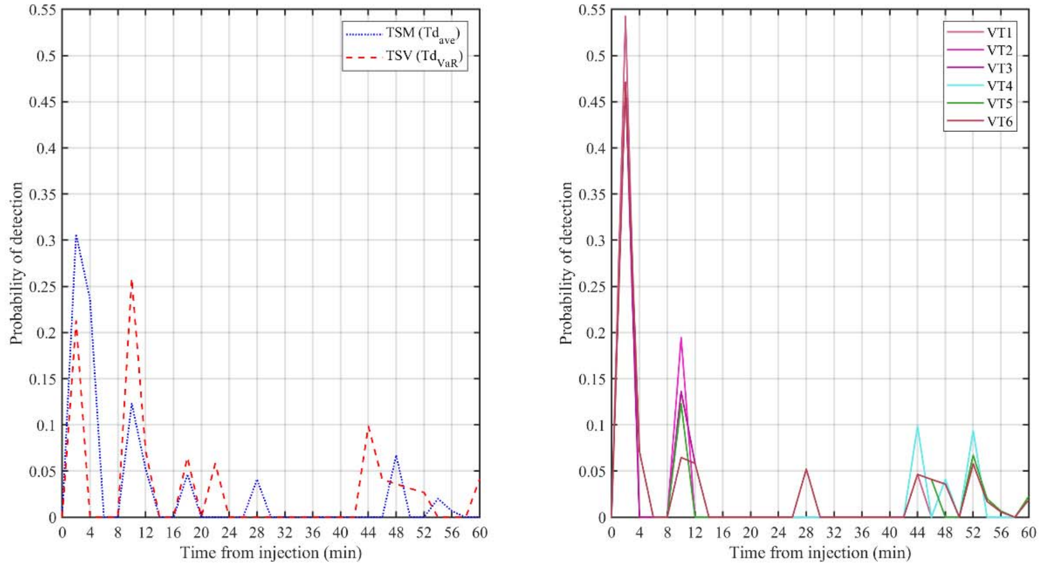


Fig. S9. Probability distribution of time to detection for CWS with 9 sensors designed by TS (left) and VT (right).

According to the TOPSIS rankings of the both models' results (Table S5), there are at least two CWS designs from VT model which have better performance with respect to the defined criteria compared to those of TS model (i.e. the best ranks of TS model's designs are 3rd for CWSs with 4 and 9 sensors). For CWSs with 3, 4, 5 and 6 sensors, the TS model's designs (TSM and TSV) are clearly dominated by VT4, VT2, VT5 and VT4 designs from VT model, respectively. Also, for CWSs with 7, 8 and 9 sensors, the TSMs or TSVs have only one criteria better than that of VTs, while the other criteria of VTs are better than those of TSMs and TSVs. For example, TSM design for CWS with 9 sensors have better Td_{ave} than that of VT6, while VT6 would perform better than TSM with respect to Td_{max} and Pd_{60}. It is also worth mentioning that there is a clear relationship between the rank, performance and the values of VOI of the designs. So that, TSMs and TSVs have lower values of VOI compared to VTs, while in most cases, TSMs and TSVs fall short in the preference order (TOPSIS rankings). It may seem that TSMs should at least provide superior Td_{ave} to VTs, because TS model is single-objective and should indeed find the optimal Td_{ave}. The reason is that, according to TS's Users' Manuals (Berry et al. 2008, Berry et al. 2012, Janke et al. 2017) the only available optimization algorithm in GUI version of TS model is GRASP algorithm. According to the Users' Manuals, Although, Mixed-Integer Programming (MIP) algorithm which is developed by TS's developers (Berry et al. 2006) is more accurate than Greedy Randomized Adaptive Search Procedure (GRASP) algorithm, it has huge memory requirements and is very slower compared to GRASP. Also, the developers have proved that GRASP provides "good" near-optimal solutions with less memory and in the quickest way possible compared to MIP (Berry et al. 2008, Berry et al. 2012, Janke et al. 2017). Therefore, the MIP algorithm is omitted from latest release of TS model in September 2017, which is TEVA-SPOT GUI v2.3.2.

To conclude our discussion, the results show that VT model is not only quicker, more efficient and more accurate than GRASP aided TS model in meeting different criteria, but also it is more accurate from optimality point of view.

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