Similarity and Conformity Graphs in Lighting Optimization and Assessment

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Abstract. Lighting affects everyday life in terms of safety, comfort and quality of life. On the other side it consumes significant amounts of energy. Thanks to the effect of scale, even a small unit reduction of a power efficiency yields the significant energy and cost savings. Unfortunately, planning a highly optimized lighting installation is a task of the high complexity, due to a huge number of variants to be checked. In such circumstances it becomes necessary to use a formal model, applicable for automated bulk processing, which allows finding the best setup or estimating resultant installation power in an acceptable time, i.e., in hours rather than days. This paper introduces such a formal model relying on the *similarity* and *conformity graph* concepts. The examples of their practical application in outdoor lighting planning are also presented. Applying those structures allows reducing substantially a processing time required for planning large scale installations.

Keywords: graph methods · similarity graph · conformity graph · optimization · complexity

1 Introduction

The growing civilization needs require making decisions quickly. Additionally, such choices should be based on the real data. In many cases, however, it is not possible to obtain those data on demand. In such situations the lacking information is estimated by human's intuition or expertise. A time pressure and lack of hard data cause our decisions to be influenced by a social environment, short-term needs or opinions of others. As a result, this choice is not optimal in many cases. These problems are referred to as the cognitive traps and they are discussed in multiple works [1]. The matter becomes more complicated if decisions impact the future and when that influence is broad, for example in the scale of a city, region or country. One of such areas is a public lighting which influences not only a quality of life and safety of people but also the energy balances of municipalities. We can observe a growing power consumption, which is caused, among others, by the increasing use of light [8, 5, 20]. This also means that the percentage of electric energy we use for public lighting has a significant share in the overall volume of greenhouse gases being produced [16].

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The use of efficient LED (*light-emitting diode*) light sources gives a power usage reduction of the order of 40 - 60% [11], compared to the high-intensity discharge (sodium) lamps. The right choice of optimal installation parameters, however, can result in a much greater, spectacular reduction reaching up to 80% [15, 16]. Those savings can play a key role in terms of the further investments. In the case of medium sized cities, the cost of electricity for lighting often exceeds 1 million euro which gives € 2,000 of annual savings, at this rate of power reduction. This budget can be used for financing other related works. For that reason it seems reasonable to carry out a citywide investment to maximize the savings which can cover either some further works in other areas or a current investment, when made in the ESCO (*energy service company*) financing model. It is therefore crucial to assess very quickly the cost of an investment itself and the potential rate of return. Unfortunately, preparing all required photometric projects and thus estimating investment costs is often a long-term process burdened with additional costs. Analysis of investments that have taken a place in the city of Cracow, Poland, in recent years, shows that the time of preparation of a single photometric project for 3,741 lighting points takes 3-10 weeks. By extrapolating it to the total number of city lights in Cracow (approx. 70,000) we can estimate the time required for financial analysis of a citywide investment at the level of at least 56 weeks of continuous (24/7) calculations, which is over the year. In the real life cases such times are utterly unacceptable.

It is neither possible to point precisely which city area should be the subject to a planned investment and in what order, nor to select the scope of a modernization (e.g., only fixtures and arms are replaced, while poles remained unchanged). Usually an estimation is made on the basis of available fixture powers, which is not the best approach in many cases. It is crucial to develop some indirect methods allowing to estimate as quick as possible, expected outlays and the return on investment (ROI). This paper introduces concepts of similarity and conformity graphs, which can be used to estimate investment risk and for such a quick estimation.

The paper is organized as follows. In the next section the state of the art is presented. In Section 3 the notions of a base graph (3.1), similarity graph (3.2) and conformity graph (3.3) are introduced. The case study demonstrating application of proposed models to a real-life case, is presented and discussed in Section 4. The final section contains conclusions and proposed directions of the further research.

2 State of the art

Creating optimized, energy-efficient lighting installations was considered in numerous scientific works. One can distinguish two approaches: the first is focused on optimization of an installation parameters (e.g., fixture model, pole height) [4, 9, 10, 12–14, 17, 19], while the second one is based on lighting control tuning, i.e. adapting lighting levels to the varying conditions such as traffic flow intensity or weather conditions [2, 3, 21–23]. The main criterion is a final installation power.

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The critical issue of such an optimization, however, is the time required for completing such a project (due to related computational complexity). Also practical methods used for its completion are revealed rarely.

One of the few works which attempt to present these factors is the work [7], in which authors propose a genetic algorithm to determine exact parameters of an installation, i.e., locations of poles and pole heights. It was achieved thanks to the appropriate definition of a chromosome which contained exact pole locations and fixture mounting angles, in addition to a fixture type and a pole height. The chromosome length is dependent on a number of light points in an optimized layout, in this case, and thus it has a considerable impact on a calculation time. For the initial population of 300 chromosomes, six types of fixtures (usually one considers thousands of models, produced by several vendors) and four potential pole heights, the algorithm execution time (50 generations) was about 2.5 hours while. Obviously, with increasing number of fixture models and enlarged street area, the computation time raised to 4 hours (see Table 1).

Table 1. Times required for finding the optimal design, when using a genetic algorithm (see [7]).

	Situation 1 (Parking)	Situation 2 (Handball court)
Problem space	6 fixture types	14 fixture types
Illuminated surface	800 m^2	1056 m^2
Number of "generations"	50	10
Time taken to find a solution	2.5 hours	4 hours

The long solution search times, as those seen above, enforce developing more efficient calculation methods. The above example shows that the GA-based approach fails when preparing a city-scale lighting design: the required time is not acceptable. When analyzing large investments (tens of thousands of streetlights), processing time is a factor of the great importance for quick decision making. The optimization methods presented in [15, 18] allow to shorten this time. It is not enough, however, for making a quick choice. Therefore, the in-depth research work on this area becomes crucial. Developing algorithms which allow preparing a project with less accuracy but with a known estimated power, in a few hours instead, can bring practical benefits. The structures of similarity and conformity graphs, extending the graph concept introduced in [18, 6], are proposed in the next section. Methods of their processing are also discussed.

3 Graph models

Before defining main graph structures, i.e., *similarity* and *conformity graphs*, it is necessary to introduce the generic structure storing information related to a lighting infrastructure. It is referred to as a *base graph*.

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3.1 Base Graph

Definition 1. ***Base graph*** *(abbrev. BG) is a graph of the form:*

$$G = (V, E, \Sigma, \Gamma, type, attr),$$

where:

- *V is a finite, non-empty set of graph nodes,*
- *E is a finite set of edges,*
- *Σ is a set of node types,*
- *Γ is a set of edge types, where $\Sigma \cap \Gamma = \emptyset$,*
- *$type : V \cup E \rightarrow \Sigma \cup \Gamma$ is a function that returns the type of a given node/edge: $type(V) = \Sigma$, $type(E) = \Gamma$,*
- *$attr$ is a function that returns a set of attribute types for a given node/edge type.*

In order to represent a lighting installation the following types, shown in Table 2, are ascribed to vertices of an infrastructure BG. Each node can be

Table 2. Exemplary node types (elements of the Σ set) of an infrastructure graph

Physical entity	Node type	Description
Street/area	U	Type representing the illuminated region
Segment	S	Street subarea (when street geometry varies)
Lighting point	L	Street luminaire
Fixture Type	F	Fixture
Pole	P	Luminaire's pole
Arm	R	Luminaire's arm

incident with an edge of a type from Γ which represents a relationship between two nodes. For instance B - "belongs to", "illuminates", "depends on" etc.

Example. The example of a scene consisting of a street and its lighting infrastructure, is shown in Figure 1. It is compound of four street segments (S1, S2, S3, S4) having a common layout but different lighting installations, in terms of geometry properties. Each segment is assigned with at least one group of lamps (CL1, CL2A, CL2B, CL3, CL4). Those groups are the subject to optimization. The entire scene is represented by the base graph shown in Figure 2. To improve the readability we neglected edge labels on that.

As shown in Figure 1 segments S1 and S3 are *very similar* not only in terms of the street geometry but also due to the *similar* lighting installation layouts (e.g., nearly identical lamp spacings). Thus an optimal setup found for the installation {1.A, 1.B, 1.C} would be applicable to {3.A, 3.B} as well. There arises a question how to assess whether two lighting situations are *similar* to each other and how to

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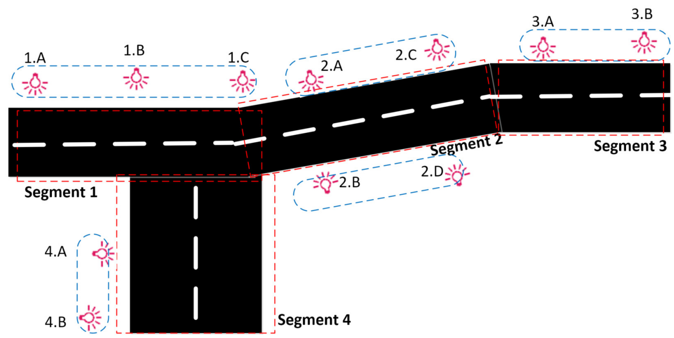

Fig. 1. The sample lighting situation

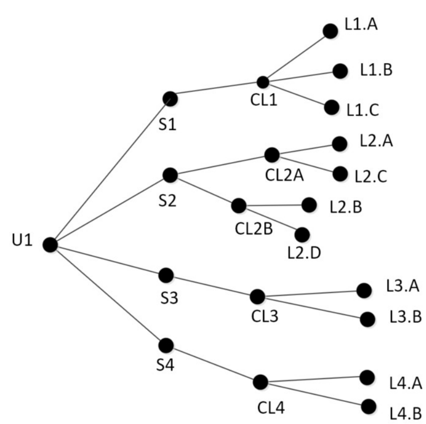

Fig. 2. Base graph representation of the scene shown in Figure 1

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quantify this *similarity*. In other words: does there exist any metrics, in the space of base graphs, which would be applicable for lighting situation comparison.

The answer to this question is affirmative. In the next subsections we introduce the notion of a similarity graph.

3.2 Similarity graph

A similarity graph is a base graph which contains edges of a specific type, $K \in \Gamma$, referred to as *similarity edges*, connecting nodes of the same type (say, two S-type nodes), with an attributing function $attr$, such that $attr(K) = g \in \mathcal{D}^{\Sigma}$, where $\mathcal{D} = \{f | f : V \times V \longrightarrow [0, 1] \wedge f(x, y) = f(y, x)\}$ is a set of functions which quantify similarity of node attribute values.

Example. Let us consider the following example to clarify this idea. Suppose $e = \{u, v\} \in E$, $type(e) = K$ and $type(u) = type(v) = S$ with a road width $W \in attr(S)$. As said, a type of the edge e is K and its attribute value is a function f which for two vertices of the same type, being endpoints of e (here: u and v) returns a number between 0 (no similarity between u and v) and 1 (full similarity between u and v). If a considered attribute is a road width, W, for the segment type (S) then f can be defined as:

$$f(u, v) = e^{-|w_u - w_v|},$$

where w_u, w_v denote segment widths for u and v respectively.

It should be emphasized that the form of an f function strongly depends on a context. Even for a single object type, e.g., S, it can have various forms, dependently on an attribute which is actually considered. In particular, one can apply $f \in \mathcal{D}$ which depends on several attributes of a node, say road width, number of lanes, surface properties and average daily traffic flow.

The formal definition of a similarity graph is given below:

Definition 2. ***Similarity graph*** *(abbrev. SG) is a base graph such that there exists $K \in \Gamma$ and*

1. $e = \{u, v\} \in E \subseteq \mathcal{P}_2(V) \wedge type(e) = K \implies type(u) = type(v)$,
2. $attr(K) = g \in \mathcal{D}^{\Sigma}$, *where* $\mathcal{D} = \{f | f : V \times V \longrightarrow [0, 1] \wedge f(x, y) = f(y, x)\}$.

An edge e satisfying 1 is referred to as a similarity edge. *$\mathcal{P}_2(V)$ denotes all two element subsets of 2^V and $V, E, \Sigma, \Gamma, type, attr$ were defined in Definition 1.*

A sample similarity graph for the representation shown in Figure 2 is presented in Figure 3. The values of some exemplary function f are marked alongside similarity edges (dashed lines). Only similarity edges connecting nodes of the type S are considered here.

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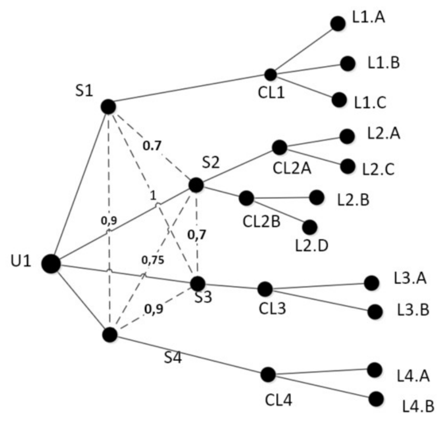

Fig. 3. Similarity graph with similarities among road segments (see Figure 2)

3.3 Conformity graph

As mentioned previously, installations for two (or more) similar lighting situations can be designed once. It reduces an overall preparation and cost assessment times. To achieve that, however, it is necessary to match all *similar* nodes, where similarity will be measured using functions from the $\mathcal{D}$ set introduced in Definition 2. To simplify that process we use a *conformity graph* defined below.

Definition 3. ***Conformity graph*** *(abbrev. CG), is a weighted similarity graph (see Definition 2) such that:*

1. $u, v \in V \implies type(u) = type(v)$,
2. $a, b \in \Sigma \implies attr(a) = attr(b)$,
3. $e \in E \implies type(e) = K \in \Gamma$ *and an edge weighting function* w*: (i)* $w : E \longrightarrow [0, 1]$*, (ii)* $attr(K) = w$,

where $V, E, \Sigma, \Gamma, K, type, attr$ *were defined in Definitions 1 and 2.*

In order to create a conformity graph we proceed following steps, starting from an initial similarity graph G_0, such as the one shown in Figure 3, for instance.

Step 1 Select a desired node type $\mathbf{X}$ (say, $\mathbf{X} = S$). Set a **similarity threshold** value, $\mathbf{t} \in [0, 1]$. Please note that an assumed value of $\mathbf{t}$ is a subject to an arbitrary decision, depending on a particular problem. For instance, in some cases we can admit even moderate disturbances in lamp spacings, what is reflected in a lower $\mathbf{t}$ value. It should be also noted that similarity between two nodes, say u and v, is tested against $\mathbf{t}$ using an $f(u, v)$ function value (see Definition 2).

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Step 2 Remove all nodes of types other than $\mathbf{X}$ from G_0, together with incident edges. *Note*: At this moment we obtain a clique, G_1, with weighted edges (see Figure 4).

Step 3 Find a maximum spanning tree, G_2, for the clique G_1. *Note*: That step, which can be performed using the modified Kruskal algorithm, is not deterministic, as several maximum spanning trees may exist for a single G_1.

Step 4 Remove all edges from G_2, for which $w(e) < \mathbf{t}$.

In Figures 5a, 5b and 5c there are shown conformity graphs obtained for three similarity thresholds: $\mathbf{t}_1 = 0$ (no constraints are imposed on similarity), $\mathbf{t}_2 = 0.9$ and $\mathbf{t}_3 = 1$ (strict object similarity) respectively.

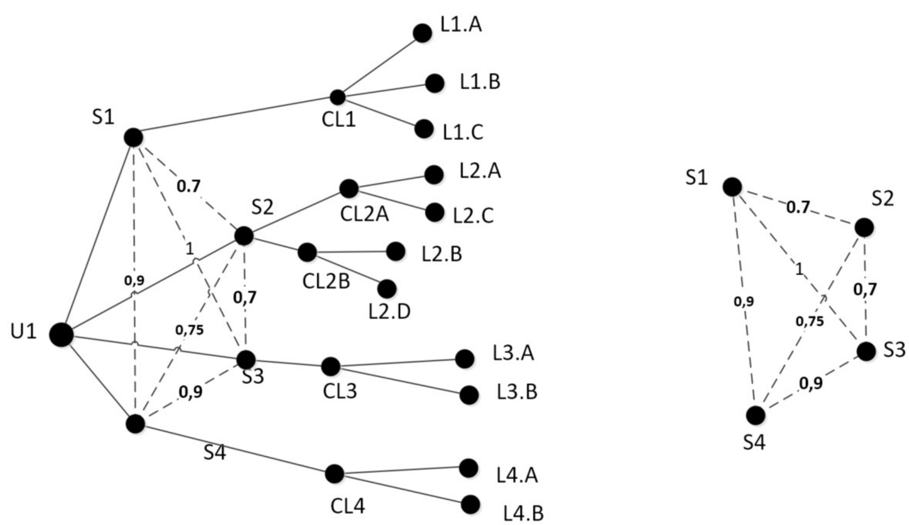
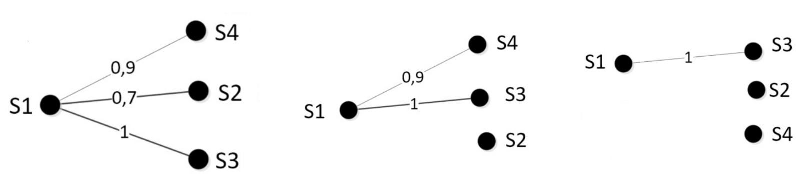


Fig. 4. Step 2 of the conformity graph creation process



(a) $\mathbf{t}_1 = 0$ (b) $\mathbf{t}_2 = 0.9$ (c) $\mathbf{t}_3 = 1$

Fig. 5. CGs with various similarity thresholds

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In the first of the above cases there are no limitations regarding similarity among segments. This implies that a lighting installation setup found for the segment $S1$ will be replicated to installations assigned to all other segments, namely, $S2, S3, S4$. Obviously, it may cause potential over- or under-lighting. The intermediate scenario, $\mathbf{t}_2 = 0.9$, represent the situation of the controlled replication of solutions among particular segments. The general rule is that reducing similarity threshold affects a confidence to the replicated solution quality but a benefit is the reduced preparation time. The trade-off between both determines a value of $\mathbf{t}$. In turn, the other extreme case, $\mathbf{t}_3 = 1$, reflects the situation when we reuse existing solution if and only if there is a full conformity between two lighting situations (identical street geometries, lamp spacings, pole heights etc.). Although it does not allow to reduce significantly a computation time, unless there are multiple uniform lighting situations, it is guaranteed that solutions can be safely replicated among connected nodes.

4 Case study

In this section application of similarity and conformity graphs in a real-life lighting installation retrofit process will be presented. The case we focus on is the investment carried out in the city of Cracow, Poland. The subject of modernization were 3,741 streetlights (approx. 5% of all streetlights in Cracow) located in the city center area (see Figure 6). Its objective was replacing existing sodium fixtures with LED-based ones. The expected result was the power usage reduction which had reached about 72%. The achieved money savings were at the same level. The lighting project preparation took over two months for this investment. Although the final result was satisfying, in terms of the power balance and financial goals, an investment's bottleneck was just the design process: note that only 5% of streetlights was modernized.

The analysis presented below gives an answer whether the process can be carried out faster. If we are able to shorten it, we will benefit from possibility of investigating several alternative setup variants, based on various combinations of fixtures, poles, arms and so on. Thus the final beneficiary is offered with a range of available options which can be selected dependently on actual business preferences and needs.

4.1 Optimization process and its parameters

For the given investment 662 street segments (lighting situations) were considered. Figure 6 shows the investment scope. All segments are marked with individual colors.

The goal of an optimization is selecting such values of particular lighting infrastructure parameters (see Table 3) that the resultant power usage is minimized.

In this case we also consider changing lamp positions (lamp spacings and setbacks), which is the extremely rare scenario in real-life retrofits.

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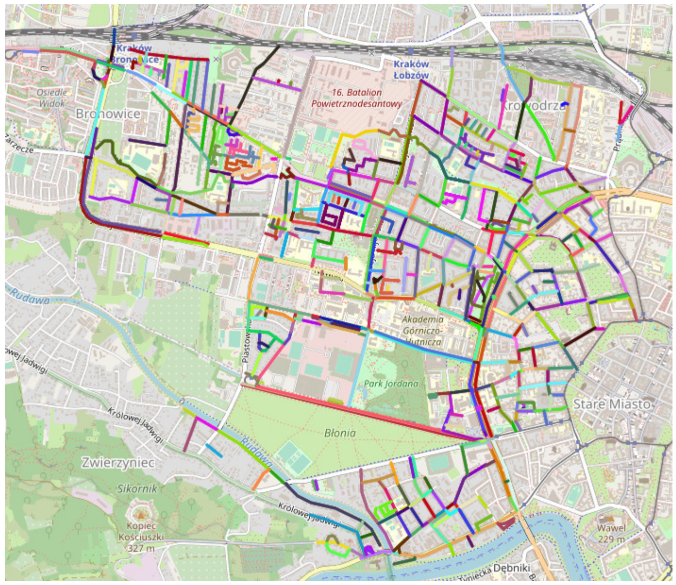

Fig. 6. The investment scope

Due to the financial constraints, the real-life investments are usually limited to changing fixtures and arms, sometimes the poles (lamp dimming and changing a mounting angle are obviously cost-free). The side effect of this limitation is less power usage reduction, compared to the full optimization. Performing a full optimization is much more complicated due to the time overhead but it offers a test bed for application the methods based on similarity and conformity graphs.

All parameters which were used in searching the optimal installation are summarized in Table 3. They produces the collection of 10,510,937,500 variants for a single segment only. It should be emphasized that the optimization engine used for calculations did not perform a brute force method but highly advanced methods and heuristics which are beyond the scope of this work. Finding the optimal setup for the entire considered investment area took about 8,220 minutes, on a single machine. The resultant power was 99.8 kW.

4.2 Application of similarity and conformity graphs

Our goal, in this subsection, is application of similarity and conformity graphs, and thus reducing project preparation time. We also want to investigate how does a similarity threshold (see Subsection 3.3) value affects resultant installation power, solution quality and calculation time.

To answer those questions the light infrastructure was modeled by the base graphs. Each of 662 street segments had its BG representation, disjoint with other ones (it was assumed that neither lamp illuminates two lighting situations). Then similarity measures among segments were determined to obtain

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Table 3. Optimization parameters

	From	To	Step	Number
Luminous flux dimming	1%	100%	1%	100
Fixture mounting angle	0°	30°	1°	31
Arm length	0 m	2 m	0.5 m	5
Lamp setback	0 m	2 m	0.5 m	5
Mounting height	6 m	12 m	1m	7
Lamp spacing	30 m	60 m	1 m	31
Fixtures types	n/a	n/a	n/a	625

corresponding similarity graph. Such a SG was ready to generate CGs for subsequent threshold values between 0.50 and 1.00 (including).

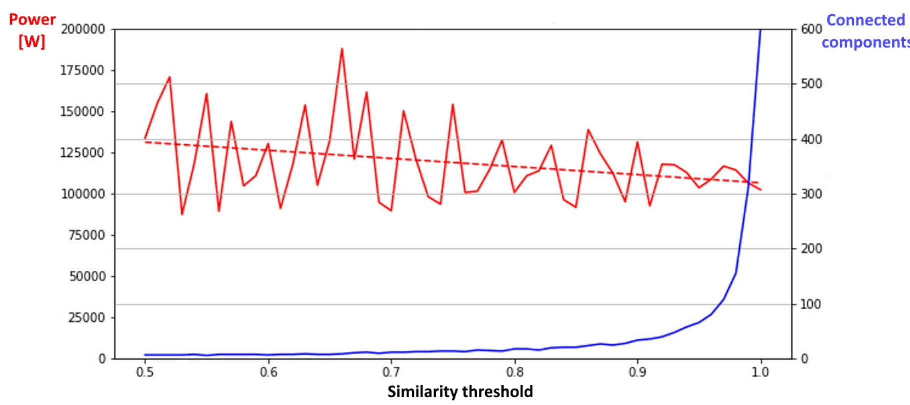

Fig. 7. Estimated resultant power of the installation and number of connected components of the conformity graph as a function of similarity threshold

After performing the series of calculations, we obtained the characteristics shown graphically in Fig. 7. Detailed results are presented in Table 4.

As shown previously, growing threshold value results in increasing number of connected components of a conformity graph.

When using the described method with the threshold value $\mathbf{t} = 1$ we get the same final installation's power as for the standard approach, namely 99.8 kW. The calculation time, however, is 7,405 min. vs 8,220 min. for the standard method (i.e., its is 13.5 hours shorter). This is because 60 of 662 initial segments had strictly similar neighbors (in the sense of CG vertex neighbors) with the same street geometry, so they inherited their solutions, without performing redundant optimization.

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Table 4. Detailed results using different conformity limit.

Similarity threshold **t**	Number of CG connected components	Estimated power [kW]	Power overhead*	Calculation time [min]
0.50	6	133.6	33.9%	74
0.60	6	134.3	34.6%	74
0.70	11	100.1	0.3%	135
0.80	17	108.2	8.4%	209
0.90	33	117.3	17.2%	406
0.95	65	107.0	7.2%	800
0.97	107	108.7	8.9%	1316
0.98	155	107.9	8.1%	1907
0.99	310	105.4	5.6%	3813
1.00	602	99.8	0.0%	7405

* The overhead relative to the optimal solution ($\mathbf{t} = 1.00$)

It should be noted that lowering the threshold by 5%, to $\mathbf{t} = 0.95$, reduces the calculation time to 800 minutes (approx. 13 h 20 min) which is $\frac{1}{10}$ of the standard method calculation time, for the power overhead lower than 10%. This value is fully acceptable for estimating a final power of the installation.

5 Conclusions

In this work we present similarity and conformity graph concepts, which may be used for assessment purposes in soft computing problems, characterized by high complexity. One of the field of their application is outdoor lighting planning/retrofitting.

In the paper we also present the case study of the lighting infrastructure modernization performed in the city of Cracow, Poland, on 3,741 streetlights illuminating 662 lighting situations. By applying the proposed approach we reduced the design preparation time by 10, with only 10% worse power efficiency, which is acceptable rate in the considered context. The SG/CG-based method allows performing *what if* analyses as well. In this case, a decision maker can choose a fixture type yielding the best power usage reduction or to select streets for which a planned investment will give the best return on investment rate.

Analyzing test results we can see that although an obtained power efficiency can be worse compared to the optimal one, we get a result in hours rather than in days.The right choice of the similarity functions and thresholds is the important factor. Further analysis of these seems to be necessary.

The presented concept is also an outline for creating an agent system that would offer even faster estimation. The use of parallel processing might enable receiving initial estimates in a time comparable to the real time.

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