Applied Computer Systems
ISSN 2255-8691 (online)
2026, vol. 31, no. 1, pp. 74–82
https://doi.org/10.2478/acss-2026-0007
https://content.sciendo.com

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Linear Programming Transportation Assignment Problem for Parametric Information-Decentralised Energy Market Model

Vadim Romanuke*
Polish Naval Academy, Gdynia, Poland

***Abstract* — A linear price-based transportation model for energy allocation in decentralised energy markets with multiple prosumers and consumers is studied. The centralised formulation minimizes the aggregate difference between generation costs and local consumer prices under supply and demand constraints. To model limited information and reduced coordination, a parametric decentralised variant is introduced, where consumers are clustered into *K* groups, and prices are averaged within *K* clusters. Consumer clustering is based on price similarity. The proposed approach treats decentralisation as a tunable structural parameter rather than a binary rule. Computational experiments across varying market sizes demonstrate that clustered configurations frequently outperform the fully individualized pricing regime in terms of the objective value, especially in unfavourable market conditions. A finding is the efficiency-versus-decentralisation relationship is non-monotonic, with an instance-dependent optimal number of clusters. The results suggest that controlled price aggregation can improve market outcomes while reducing informational and computational complexity.**

***Keywords* — Clustering, consumers, decentralisation, energy market, optimal energy flow, prosumers.**

I. Decentralised Energy Market Full Information Issue

The ongoing transition of power systems toward distributed and low-carbon generation has fundamentally changed the structure of electricity markets. A growing share of energy is now produced by small-scale, geographically dispersed units, commonly referred to as prosumers, which both generate and consume electricity. At the same time, end consumers increasingly exhibit heterogeneous demand profiles and willingness to pay, driven by factors such as flexible loads, local storage, and dynamic pricing schemes. These developments motivate the study of decentralised energy markets, where allocation and pricing decisions must be made under limited information and reduced coordination [1], [2].

From a computational perspective, many energy allocation problems can be formulated as linear or convex optimisation models, allowing efficient solution even for moderately large systems. In particular, linear programming formulations resembling transportation or assignment problems have been widely used to model energy flows between prosumers (generators) and consumers, subject to capacity and demand constraints [3], [4]. Such models provide transparent welfare interpretations and are well suited for scenario-based analysis. However, they typically rely on full information availability, assuming that a central coordinator has complete knowledge of generation costs and consumer willingness to pay [5].

In practice, full information revelation is often unrealistic or undesirable. Privacy concerns, communication costs, regulatory constraints, and strategic considerations all limit the granularity of information that can be centrally processed [6]. As a result, real-world decentralised markets operate with aggregated, distorted, or incomplete signals, which may lead to suboptimal allocations when compared to a fully centralised benchmark [1], [4]. Quantifying the efficiency loss induced solely by information decentralisation therefore remains an important and practically relevant problem.

II. Motivation and Related Works

The full information issue of the decentralised energy market is to be addressed by starting from a centralised linear programming formulation of an energy allocation problem between prosumers and consumers, referred to as the Linear Programming Transportation Assignment Problem (LPTAP). The centralised model serves as a welfare-optimal benchmark under complete information [3]. Building on this baseline, a parametric decentralised variant, denoted for further reference as LPTAP-D, in which consumer willingness-to-pay information is aggregated into a set of *K* representative signals prior to optimisation. Parameter *K* controls the level of information resolution available to the coordinating entity, ranging from a fully aggregated market signal to complete information revelation. In the case of complete information, *K* is the total number of consumers in the market [1], [3], [7].

A parametric information-decentralised energy market model (PIDEMM) is based on the LPTAP-D whose formulation and computational analysis must preserve feasibility and linear structure while isolating the impact of information loss on allocative efficiency. To enable a controlled evaluation of the efficiency gap attributable to decentralisation, number *K* is to be systematically varied and the resulting outcomes are to be compared to the centralised benchmark (i.e., to the LPTAP).

*Corresponding author's e-mail: romanukevadimv@gmail.com
Article received 2026-02-12; accepted 2026-05-05

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The approach is fully deterministic (although the data for LPTAP-D will be generated randomly, this is controlled by pseudorandom number generator seeding [8]), computationally tractable, and readily implementable using standard optimisation tools [7].

Research on energy market modelling has produced a broad spectrum of approaches for allocating energy between producers and consumers under technical and economic constraints. A significant portion of this literature relies on optimisation-based formulations, particularly linear and convex programming models, due to their transparency, scalability, and suitability for system-level analysis [9], [10]. In these models, energy flows are typically determined by minimising production costs or maximising social welfare subject to capacity and demand constraints, often resulting in formulations structurally equivalent to transportation or assignment problems [11].

Within this class of models, centralised market-clearing mechanisms remain dominant. Centralised formulations assume that a system operator or coordinator has full access to generation costs, consumer demand, and willingness-to-pay information, enabling welfare-optimal allocations under complete information [12], [13]. While such models are valuable as benchmarks, their assumptions are increasingly questioned in the context of decentralised energy systems, where prosumers and consumers are geographically dispersed, information is privately held, and communication is imperfect [9], [10], [14].

To address these limitations, several strands of research have explored decentralised and peer-to-peer (P2P) energy trading mechanisms. These include agent-based models, double auctions, and negotiation-based frameworks, often emphasizing market participation, incentive compatibility, or local trading structures [15], [16]. Although these approaches provide important insights into decentralised coordination, they frequently rely on complex behavioural assumptions, iterative protocols, or non-convex formulations, which may limit their transparency and computational tractability for large-scale or scenario-based studies.

Another prominent direction focuses on algorithmic decentralisation, where centralised optimisation problems are decomposed using methods such as the alternating direction method of multipliers or consensus-based algorithms [6], [17]. In these works, decentralisation is primarily computational: agents solve local subproblems while exchanging messages to achieve global consistency. Importantly, such approaches often still assume truthful and complete information sharing among agents, thereby addressing scalability rather than informational decentralisation.

Relatively few studies isolate the impact of information constraints on allocative efficiency. Some works investigate price aggregation, demand clustering, or anonymisation mechanisms to preserve privacy or reduce communication overhead, typically analysing their effects on market outcomes or equilibrium properties [3], [9], [18], [19]. However, these contributions are often embedded in specific market designs or dynamic pricing schemes, making it difficult to disentangle the pure effect of information loss from other structural or behavioural factors. Machine learning methods, excellently forecasting demand and price [1], [20], [21], primarily focus on prediction or adaptive decision-making rather than explicit optimisation of allocation under structural constraints.

In contrast to the above approaches, the present work focuses on a parametric information-decentralised formulation that preserves the linear structure and feasibility of a centralised allocation model while explicitly controlling the degree of information aggregation. By introducing the LPTAP-D family of problems, where parameter K represents the number of distinct price signals available to the coordinator, decentralisation is modelled solely through information resolution, without altering constraints, agent behaviour, or solution methodology. This allows for a controlled and interpretable evaluation of efficiency losses attributable exclusively to information aggregation, bridging the gap between fully centralised benchmarks and highly decentralised market mechanisms.

III. Centralised LPTAP Model

Consider a system consisting of M prosumers indexed by $i = \overline{1, M}$ and N consumers indexed by $j = \overline{1, N}$. Let x_{ij} denote the amount of energy supplied by prosumer i to consumer j. Each prosumer i has an available generation capacity G_i with generation cost c_i of energy unit, and each consumer j has a fixed demand requirement D_j by a local price p_j for energy unit. The local price is determined externally (for instance, via a community voting mechanism or an automated local pricing algorithm).

The centralised LPTAP is formulated as the following linear optimisation problem:

$$\min_{\left\{\{x_{ij}\}_{j=1}^{N}\right\}_{i=1}^{M}} \sum_{i=1}^{M}\sum_{j=1}^{N}\left(c_i - p_j\right)x_{ij} \tag{1}$$

subject to the prosumer capacity constraints

$$\sum_{j=1}^{N} x_{ij} \leqslant G_i \quad \forall i = \overline{1, M}, \tag{2}$$

and the consumer demand satisfaction constraints

$$\sum_{i=1}^{M} x_{ij} \geqslant D_j \quad \forall j = \overline{1, N} \tag{3}$$

with non-negativity conditions

$$x_{ij} \geqslant 0 \quad \forall i = \overline{1, M} \text{ and } \forall j = \overline{1, N}. \tag{4}$$

The centralised LPTAP by (1)–(4) will serve as the reference benchmark for the decentralised variants. Unlike standard centralised allocation models where a system operator directly assigns consumption quantities to consumers, the formulation by (1)–(4) explicitly models bilateral energy flows between prosumers and consumers, reflecting ownership and trading structure.

The objective function by (1) aggregates net trading costs across all bilateral prosumer-consumer links. For each unit of energy transferred from prosumer *i* to consumer *j*, the term $c_i - p_j$ represents the difference between the generation cost and the local consumer price. Minimising this quantity corresponds to assigning energy flows so that low-cost prosumers preferentially serve high-price consumers, subject to physical feasibility. It is important to remember that $\{p_j\}_{j=1}^{N}$ prices are not decision variables of the centralised problem. They are treated as exogenous parameters, reflecting decentralised or local pricing mechanisms. In this sense, the centralised LPTAP does not compute equilibrium prices but rather computes an efficient flow pattern conditional on a given price profile.

The centralised LPTAP provides a computationally tractable benchmark that includes information on prosumers, consumers, costs, and demand. Because all flows are optimised jointly, the solution yields the minimal possible aggregate net cost compatible with the imposed prices and constraints. This formulation plays a dual role herein. First, it establishes a performance upper bound against which decentralised implementations can be evaluated. Second, it provides a natural structural template for decentralisation: by restricting information, aggregating prices, or clustering consumers, one can derive reduced-complexity variants (most notably the PIDEMM based on the LPTAP-D) whose efficiency loss relative to the centralised benchmark can be quantified.

While the centralised LPTAP yields an allocation that is optimal under full information, its implementation presupposes complete knowledge of individual consumer prices and demands, as well as centralised coordination of all bilateral energy flows. Such assumptions are increasingly misaligned with the operational realities of modern decentralised energy markets, where pricing information is often local, partially private, noisy, or formed through collective mechanisms rather than centralised optimisation.

In practice, consumer prices frequently emerge at an aggregated level, for example, through community voting, local market clearing, or intermediary aggregators acting on behalf of groups of consumers. This naturally leads to a reduction in price resolution, whereby individual willingness-to-pay values are replaced by representative prices shared within consumer groups. From an optimisation perspective, this price aggregation can be viewed as an intentional restriction of information, trading off allocative efficiency for reduced informational and organisational complexity.

The centralised LPTAP provides a natural structural template for studying this tradeoff, as prices enter the objective function linearly and separably. By clustering consumers according to similarity in willingness to pay and assigning each cluster a representative (e.g., centroid-based) price, one obtains a family of decentralised models parameterized by the number of clusters *K*. The resulting LPTAP-D formulation will interpolate smoothly between the fully centralised benchmark (when $K = N$) and a highly decentralised regime with minimal price differentiation (when $K = 1$), thereby enabling a systematic analysis of efficiency losses induced by decentralisation and information coarsening.

IV. PIDEMM

In decentralised energy markets, individual consumer prices are often not directly observable or actionable at the system level. Instead, prices may be formed or communicated at an aggregated level, for example, through local market clearing, community voting, or intermediary agents representing groups of consumers. To model this phenomenon, consumers are grouped into *K* clusters based on similarity in their local willingness to pay. Let the set of consumers $S = \{s_j\}_{j=1}^{N}$, which can be represented by the respective prices $\{p_j\}_{j=1}^{N}$, be partitioned into *K* disjoint clusters

$$\{S_k\}_{k=1}^{K} \text{ by } 1 \leqslant K \leqslant N \tag{5}$$

such that each consumer belongs to exactly one cluster, i.e.,

$$S = \bigcup_{k=1}^{K} S_k \text{ by } S_k \bigcap S_l = \varnothing$$
$$\forall k = \overline{1, K} \text{ and } \forall l = \overline{1, K} \text{ for } l \neq k. \tag{6}$$

The clustering is performed in the space of local prices (or willingness-to-pay values), with the objective of minimizing within-cluster heterogeneity. In computational experiments, this is naturally implemented using centroid-based clustering methods [22], such as *k*-means [23], which yield representative cluster prices.

For each cluster *k*, a representative price $\overline{p}_k$ is computed (an effective price), for instance as the arithmetic mean of the prices of consumers belonging to that cluster. All consumers within cluster k are then treated as sharing this common price, reflecting aggregated or collective price signals. Effective prices $\{\overline{p}_k\}_{k=1}^{K}$ are the only prices visible to the coordinator.

Along with price aggregation (averaging), consumer demands are aggregated at the cluster level. Let

$$\overline{D}_k = \sum_{j \in S_k} D_j \tag{7}$$

denote the total demand of cluster S_k. This aggregation reflects the assumption that, from the perspective of prosumers or a coordinating mechanism, only the total demand of each consumer group is relevant, rather than individual consumer requirements.

As a result, the decentralised system is characterized by *M* prosumers with capacities $\{G_i\}_{i=1}^{M}$ and unit costs $\{c_i\}_{i=1}^{M}$, and *K* consumer clusters with aggregated demands $\{\overline{D}_k\}_{k=1}^{K}$ by (7) and representative prices $\{\overline{p}_k\}_{k=1}^{K}$. Let y_{ik} denote the energy flow from prosumer i to consumer cluster S_k. The LPTAP-D is then formulated as the following linear optimisation problem:

$$f(K) = \min_{\{\{y_{ik}\}_{k=1}^{K}\}_{i=1}^{M}} \sum_{i=1}^{M} \sum_{k=1}^{K} (c_i - \overline{p}_k)\, y_{ik} \tag{8}$$

subject to the prosumer capacity constraints

$$\sum_{k=1}^{K} y_{ik} \leqslant G_i \quad \forall i = \overline{1, M}\,, \tag{9}$$

and the cluster-level demand satisfaction constraints

$$\sum_{i=1}^{M} y_{ik} \geqslant \bar{D}_k \quad \forall k = \overline{1, K} \tag{10}$$

with non-negativity conditions

$$y_{ik} \geqslant 0 \quad \forall i = \overline{1, M} \text{ and } \forall k = \overline{1, K}\,. \tag{11}$$

The LPTAP-D by (8)–(11) is the PIDEMM mirroring the structure of the centralised LPTAP by (1)–(4) while explicitly reflecting reduced price resolution and aggregated demand representation. The decision variables now correspond to energy flows between prosumers and consumer clusters rather than individual consumers. Parameter K controls the degree of decentralisation. It parameterizes the model and captures varying degrees of decentralisation in price formation and coordination. When K equals the number of consumers, each cluster contains exactly one consumer, and the LPTAP-D formulation by (8)–(11) coincides with the centralised LPTAP by (1)–(4). Conversely, when $K = 1$, all consumers are represented by a single aggregated price and demand, corresponding to a highly decentralised regime with minimal price differentiation. Intermediate values of K represent partial decentralisation, where limited price and demand information is available. By varying parameter K, one can systematically study the tradeoff between allocative efficiency and informational simplicity, and quantify the efficiency loss induced by consumer aggregation relative to the centralised benchmark.

V. Computational Experiments

Let the number of prosumers vary between 3 and 20: $M = \overline{3, 20}$. In general, the number of consumers must not depend on the number of prosumers, so let the number of consumers vary between 3 and 20 as well: $N = \overline{3, 20}$. The available generation capacity G_i of prosumer i is an integer randomly chosen between 26 and 75 (kWh). The fixed demand requirement D_j of consumer j is randomized similarly: it is an integer randomly chosen between 26 and 75 (kWh). The generation cost c_i of energy unit, as well as the local price p_j for energy unit, is a real number randomly chosen between 0.05 and 0.15 (€/kWh). An instance of the PIDEMM at a given pair of $\{M, N\}$ is generated 100 times by different pseudorandom number generator seeds. This ensures statistical consistency and relative stability of the solutions of LPTAP-D by (8)–(11) for $K = \overline{1, N}$. The number of clusters that minimizes the minimum value $f^*(K)$ of objective function (8) is denoted by K^*.

An $\{M, N\}$-lattice with generally summarized solution results is presented in Fig. 1, where no-solution and all-solved regions are contoured. The numerical map shows that the LPTAP-D is usually solvable by $M > N$ and may be solvable with fewer prosumers by a significantly greater number of consumers (e.g., there are 6 solutions at $M = 3$ and $N = 20$; 52 to 70 solutions at $M = \overline{5, 9}$ by $N = 20$).



Fig. 1. Summary of solution results of LPTAP-D by (8)–(11): red square – no solution found; green circle – the solution found; white circle – $K^* = N$; blue star – $K^* < N$. The triple of numbers above the vertex: the number of solutions, number of instances where $K^* = N$, and number of instances where $K^* < N$.

A disclosure of the $\{M, N\}$-lattice in Fig. 1 with respect to the PIDEMM instances where $K^* = N$ is presented in Fig. 2. The red square and green circle, just like in Fig. 1, imply that at least one instance occurred such that it does not have a solution and it has a solution (where $K^* = N$ or $K^* < N$), respectively.

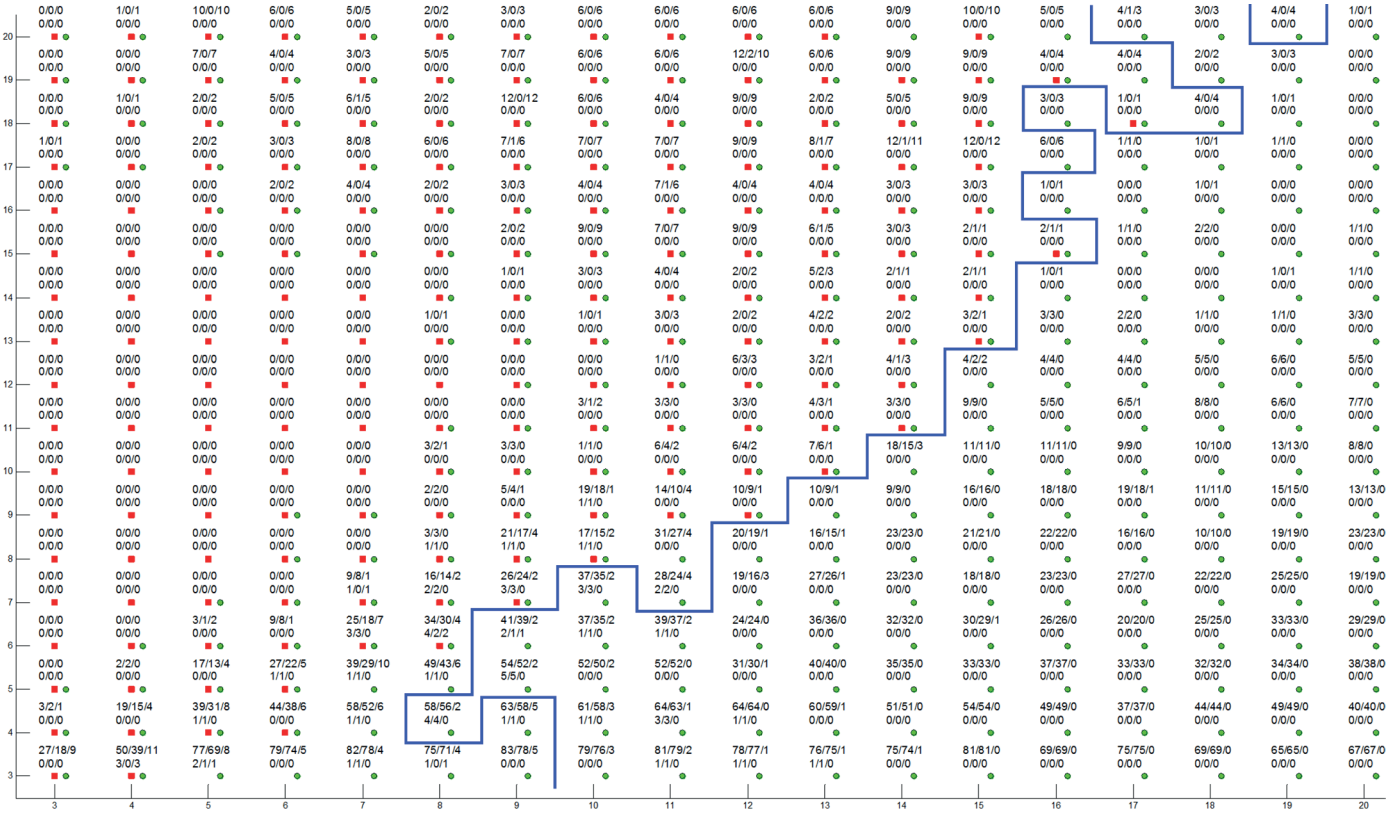


Fig. 2. A disclosure of the numerical map in Fig. 1 with respect to the PIDEMM instances where $K^* = N$. The first row of the numbers above the vertex is the number of instances where the minimized objective function (8) has the single global minimum at N consumers, the number of instances where the energy market is healthy [24], and the number of instances where the energy market is unhealthy. The second row shows the respective numbers for the case when the local minimum of objective function $f^*(K)$ over clustered consumers practically coincides with global minimum value $f^*(N)$ and the minima are equivalent.

$$f^*\left(K^*\right) = f^*(N) < f^*(K) \quad \forall K = \overline{1, N-1} \tag{12}$$

holds; the number of instances where the energy market by (12) is healthy (contoured in the all-solved region, where 0 to 3 unhealthy markets are) [24], i.e., the total energy produced by M prosumers had cost less than N consumers paid and thus

$$f^*\left(K^*\right) = f^*(N) < 0; \tag{13}$$

the number of instances where the energy market by (12) is unhealthy, i.e., the total energy produced by M prosumers had cost more than N consumers paid and thus

$$f^*\left(K^*\right) = f^*(N) > 0. \tag{14}$$

Expectedly, there are no instances with $f^*\left(K^*\right) = 0$ (such instances are unlikely for the current set-up of computational experiments), whichever K^* is. The second row of the numbers above the vertex describes the case when $K^* = N$ but minimum value $f^*\left(K^*\right)$ is sufficiently close to the minimum of objective function $f^*(K)$ over the number of clusters fewer than the number of consumers (i.e., by $K < N$). Denoting

$$f^*\left(K^{**}\right) = \min_{K=\overline{1, N-1}} f^*(K), \tag{15}$$

where minimum value (15) is reached at K^{**} consumer clusters, the sufficient closeness is read as

$$f^*\left(K^{**}\right) - f^*\left(K^*\right) < 10^{-6} \text{ by } K^* = N. \tag{16}$$

Thus, the second row of the numbers above the vertex is: the number of instances where condition (16) holds; the number of instances where the energy market by (16) is healthy, i.e., the total energy produced by M prosumers had cost less than N consumers within K^* clusters paid and thus

$$f^*\left(K^*\right) < 0; \tag{17}$$

the number of instances where the energy market by (16) is unhealthy, i.e., the total energy produced by M prosumers had cost more than N consumers within K^* clusters paid and thus

$$f\left(K^*\right) > 0. \tag{18}$$

The numerical map in Fig. 2 reveals that the number of instances where condition (16) holds (there are 56 such instances) is much less than the number of instances of the single global minimum at N consumers (there are 4587 such instances). The number of instances with the healthy single global minimum is 3956, and there are 631 unhealthy instances with the single global minimum. Roughly the same ratio of healthy-to-unhealthy instances keeps for the case of two equivalent minima by (16): 47 healthy and 9 unhealthy ones.

Hence, a single global minimum is incomparably more probable than two minima. Its healthiness is about five to six times is more probable than unhealthiness. The numerical map in Fig. 2 also reveals that the pattern of its vertex numbers distribution does not resemble that of the numerical map in Fig. 1 – fewer prosumers cannot be efficient for a significantly greater number of consumers without clustering them.

But there is another possibility – when a single global minimum is reached at $K^* < N$. A disclosure of the $\{M, N\}$-lattice in Fig. 1 with respect to the PIDEMM instances where $K^* < N$ is presented in Fig. 3. The red square and green circle still show the absence and presence of a solution (where $K^* = N$ or $K^* < N$), and the two rows of the tripled numbers above the vertex describe the features similar to Fig. 2. The first row of the numbers above the vertex is: the number of instances where objective function $f^*(K)$ has the single global minimum at $K^* < N$ consumer clusters, i.e., inequality

$$f^*\left(K^*\right) < f^*(K) \quad \forall K = \left\{\overline{1, N}\right\} \setminus \left\{K^*\right\} \tag{19}$$

holds; the number of instances where the energy market by (19) is healthy (contoured in the all-solved region, where 0 to 4 unhealthy markets are), i. e. the total energy produced by M prosumers had cost less than N consumers within K^* clusters paid and thus (17) is true; the number of instances where the energy market by (19) is unhealthy, i.e., the total energy produced by M prosumers had cost more than N consumers within K^* clusters paid and thus (18) is true. The second row of the numbers above the vertex is: the number of instances where condition

$$f^*(N) - f^*\left(K^*\right) < 10^{-6} \text{ by } K^* < N \tag{20}$$

holds, i.e., points $K = K^* < N$ and $K = N$ are practically equivalent minima; the number of instances where the energy



Fig. 3. A disclosure of the numerical map in Fig. 1 with respect to the PIDEMM instances where $K^* < N$. The first row of the numbers above the vertex is the number of instances where objective function $f^*(K)$ has the single global minimum at $K^* < N$ consumer clusters, the number of instances where the energy market is healthy, and the number of instances where the energy market is unhealthy. The second row shows the respective numbers for the case when the global minimum of objective function $f^*(K)$ over clustered consumers practically coincides with value $f(N)$ and thus the values are regarded equivalent minima.

market by (20) is healthy, i.e., the total energy produced by M prosumers had cost less than N consumers within K^* clusters paid and thus (17) is true; the number of instances where the energy market by (20) is unhealthy, i.e., the total energy produced by M prosumers had cost more than N consumers within K^* clusters paid and thus (18) is true.

The numerical map in Fig. 3 has a pattern of its vertex numbers distribution mainly resembling that of the numerical map in Fig. 1 – even fewer prosumers may be efficient for a significantly greater number of consumers if the latter are clustered. A pattern triangle of PIDEMM non-solvability is seen in the map: one side of the triangle is vertical at the fewest number of prosumers and the opposite vertex to this side "pierces" the lattice in the direction of the growing number of prosumers.

There are 17 302 PIDEMM instances solved with the single global minimum at $K^* < N$ consumer clusters. The number of instances with the healthy single global minimum at $K^* < N$ is 12 564, and there are 4738 unhealthy instances with the single global minimum at $K^* < N$. Here the ratio of healthy-to-unhealthy instances is much smaller than that for the case of the single global minimum at N consumers. Roughly the same ratio of healthy-to-unhealthy instances at $K^* < N$ keeps for the case of two equivalent minima by (20): 127 healthy and 45 unhealthy ones. Overall, 22 117 PIDEMM instances out of 32 400 ones have had solutions, so consumer clustering has been efficient in 78.23 % of the solved instances.

VI. Discussion

The computational experiments provide several nontrivial insights into the behaviour of the PIDEMM relative to its fully centralised counterpart by the LPTAP. By systematically varying the numbers of prosumers and consumers and repeatedly sampling problem instances, the experiments reveal both typical and exceptional patterns in how clustering affects market outcomes. These patterns for healthy and unhealthy markets are gathered in Tables I and II (from Figs. 1–3), respectively, along with the ratios of the centralised cases to the clustered cases. Table III shows the aggregation of the healthy and unhealthy markets.

TABLE I
LPTAP-D Solutions For Healthy Markets

Solution	Centralised (no clustering)	Consumers are clustered	Ratio
Single global minimum	3956	12564	0.314868
Practically equivalent minima by clustering and without clustering	47	127	0.370079

TABLE II
LPTAP-D Solutions For Unhealthy Markets

Solution	Centralised (no clustering)	Consumers are clustered	Ratio
Single global minimum	631	4738	0.133179
Practically equivalent minima by clustering and without clustering	9	45	0.2

TABLE III
Aggregated LPTAP-D Solutions

Solution	Centralised (no clustering)	Consumers are clustered	Ratio
Single global minimum	4587	17302	0.265114
Practically equivalent minima by clustering and without clustering	56	172	0.325581

The first striking observation is that, among instances admitting feasible solutions, outcomes in which the global minimum is attained at a clustered configuration ($K^* < N$) substantially outnumber those in which the minimum is attained at the fully individualized pricing regime ($K^* = N$). In particular, the ratio of instances with a unique minimum at N to those with a unique minimum at $K^* < N$ is approximately 0.27. This imbalance persists even when the analysis is restricted to healthy energy markets, where the optimal objective value is negative.

This empirical dominance suggests that, under random yet structurally consistent generation–demand configurations, consumer aggregation is not merely a complexity-reducing approximation but often leads to strictly better objective values. In economic terms, price aggregation frequently improves overall compensation conditions for prosumers rather than degrading them. This observation aligns with the interpretation of clustering as a regularization mechanism that smooths excessive heterogeneity in individual prices.

Separating healthy and unhealthy market instances further sharpens the picture. In healthy markets (Table I), clustered optima ($K^* < N$) appear more than three times as often as centralised optima ($K^* = N$), whereas in unhealthy markets the dominance of clustering is even more pronounced (Table II). The ratio of unhealthy centralised optima ($K^* = N$) to unhealthy clustered optima ($K^* < N$) is only about 0.13, indicating that clustering is particularly beneficial when generation costs and local prices are misaligned in a way that would otherwise lead to undercompensated energy production.

This asymmetry suggests that decentralisation via clustering may act as a stabilizing mechanism in unfavourable market conditions [6], [24]. By averaging prices within clusters, the solution of the corresponding LPTAP-D can mitigate extreme local price signals that would render energy generation economically unattractive under fully individualized pricing.

Cases involving approximate equivalence of minima are observed to be exceedingly rare, collectively accounting for less than 1 % of all solvable instances. This rarity indicates that the objective landscape typically exhibits a clear separation between the best clustered solution and the fully centralised solution, rather than a flat or degenerate structure.

From a modelling perspective, this is a favourable property: it implies that the choice between clustering and full decentralisation is usually decisive, rather than numerically ambiguous. When approximate equivalence does occur, it can be interpreted as evidence of near-homogeneous consumer structures, where price aggregation neither significantly improves nor degrades market efficiency.

Taken together, the results provide strong empirical support for the use of PIDEMM as a meaningful decentralised alternative to the centralised LPTAP. Importantly, decentralisation here does not correspond to a monotone loss of efficiency as information is coarsened. Instead, the relationship between the number of clusters and the objective value is non-monotonic, with an optimal intermediate clustering level ($K^* < N$) frequently yielding the best outcome.

This finding challenges the conventional intuition that full price individualization is always welfare-optimal. In practice, clustered pricing schemes may outperform fully personalized ones by reducing noise, dampening extreme local incentives, and enhancing coordination among consumers with similar demand profiles.

From an applied standpoint, the experimental results open several practical avenues. In market implementation, energy communities or microgrids may benefit from designing tariff structures around consumer clusters rather than individual pricing. Since the optimal number of clusters varies across instances, adaptive or data-driven clustering mechanisms could be integrated into decentralised energy platforms. Clustering substantially reduces informational and computational requirements, making the PIDEMM suitable for large-scale deployments.

Due to the limited availability of publicly accessible datasets capturing disaggregated prosumer-and-consumer interactions, the computational study has relied on synthetically generated instances. The matter is that real-world energy data are typically aggregated, proprietary, or subject to privacy constraints, and do not simultaneously provide generation costs, local willingness-to-pay, and bilateral allocation information required by the model. Moreover, synthetic data enable controlled variation of market structure parameters and facilitate systematic analysis of the proposed parametric decentralisation mechanism. The use of synthetic datasets is common in energy systems and decentralised market research, where privacy constraints and data fragmentation limit access to detailed transactional data. For example, synthetic smart meter datasets and virtual power plant simulations have been developed to emulate realistic consumption and generation patterns while preserving confidentiality [25], [26]. Similarly, Monte Carlo simulations and agent-based models are widely used to study peer-to-peer energy trading and market behaviour under controlled conditions [27], [28]. These approaches enable systematic evaluation of market mechanisms while maintaining consistency with physical and statistical properties of real energy systems.

Despite these encouraging findings, several limitations should be noted. First, the experiments rely on randomly generated instances, which, while structurally consistent, may not fully capture the statistical dependencies present in real-world energy markets. Second, the clustering procedure itself is exogenous to the optimisation problem; alternative clustering criteria or endogenous cluster formation could alter the results. Finally, the analysis focuses on static single-period optimisation, whereas real markets exhibit dynamic behaviour, learning effects, and strategic adaptation over time. Addressing these limitations constitutes a natural direction for future research and may further clarify the conditions under which decentralised clustered pricing is most effective.

VII. Conclusion

The PIDEMM introduces a decentralised variant of a linear price-based transportation approach to energy allocation, where decentralisation is implemented through consumer price aggregation and clustering. The PIDEMM allows decentralisation to be treated not as a binary choice, but as a tunable structural parameter. The computational experiments demonstrate that consumer clustering does not merely reduce informational and computational complexity, but often leads to strictly better market outcomes in terms of the objective value. In a substantial majority of solvable instances, the optimal clustered configuration (by $K^* < N$) outperforms the fully individualized pricing regime. This effect is especially pronounced in unhealthy market regimes, where clustering frequently mitigates undercompensation of energy generation. Approximate equivalence between clustered and non-clustered solutions is observed to be rare, indicating that the efficiency differences are typically decisive rather than marginal.

These findings suggest that decentralised energy markets may benefit from controlled information aggregation rather than maximal price granularity. Clustering consumers with similar willingness-to-pay values acts as a regularization mechanism that stabilizes price signals, reduces excessive heterogeneity, and improves coordination between prosumers and consumers. Importantly, the relationship between decentralisation level and efficiency is non-monotonic, implying the existence of an instance-dependent optimal clustering level.

From a practical perspective, the PIDEMM provides a tractable and flexible tool for designing pricing and allocation mechanisms in local energy markets, microgrids, and energy communities. It is particularly suitable in settings where full information disclosure is infeasible or undesirable, and where adaptive clustering can be implemented based on observed demand and price patterns. Overall, the results indicate that decentralisation through controlled aggregation is not necessarily a compromise between efficiency and complexity, but can constitute a systematic improvement over fully centralised market designs.

Several directions for future research naturally follow. First, alternative clustering mechanisms may be explored beyond centroid-based price aggregation, including endogenous or game-theoretic cluster formation. Second, extending the model to dynamic and multi-period settings would allow the study of learning, temporal coupling, and storage effects. Third, incorporating strategic behaviour of prosumers and consumers could bridge the model with equilibrium concepts from non-cooperative game theory. Finally, empirical validation using real market or smart-meter data would further assess the practical relevance of the proposed decentralisation approach.

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Vadim V. Romanuke was born in 1979. He graduated from the Technological University of Podillya in 2001. In 2006, he received the Degree of Candidate of Technical Sciences in Mathematical Modelling and Computational Methods. The Candidate Dissertation suggested a way of increasing interference noise immunity of data transferred over radio systems. The degree of Doctor of Technical Sciences in Mathematical Modelling and Computational Methods was received in 2014. The Doctor-of-Science Dissertation solved a problem of increasing efficiency of identification of models for multistage technical control and run-in under multivariate uncertainties of their parameters and relationships. In 2016, he received the status of a Full Professor.
He is a Professor of the Faculty of Mechanical and Electrical Engineering at the Polish Naval Academy. His current research interests concern decision making, game theory, semantic image segmentation, statistical approximation, and control engineering based on statistical correspondence. He is the author of 460 scientific articles, one monograph, one tutorial, and 16 methodical guidelines in Functional Analysis, Mathematical and Computer Modelling Master Thesis preparation, Conflict-Controlled Systems, Algorithms and Data Structures, Data Analysis, Master Academic Practice. Before January 2018, Vadim Romanuke was the scientific supervisor of a Ukrainian budget grant work concerning minimisation of water heat transfer and consumption.
Address for correspondence: 69 Śmidowicza Street, Gdynia, Poland, 81-127.
E-mail: romanukevadimv@gmail.com
ORCID iD: https://orcid.org/0000-0003-3543-3087