Dynamic Matching in Power Systems using Model Predictive Control

Majid Majidi
Department of Electrical and Computer Engineering
University of Utah
Salt Lake City, USA
majid.majidi@utah.edu

Deepan Muthirayan
Department of Electrical Engineering and Computer Sciences
University of California Irvine
Irvine, USA
deepan.m@uci.edu

Masood Parvania
Department of Electrical and Computer Engineering
University of Utah
Salt Lake City, USA
masood.parvania@utah.edu

Pramod P. Khargonekar
Department of Electrical Engineering and Computer Sciences
University of California Irvine
Irvine, USA
pramod.khargonekar@uci.edu

***Abstract*—Integration of distributed renewable energy sources (D-RES) has been introduced as a viable solution to offer cheap and clean energy to customers in decentralized power system. D-RES can offer local generation to flexible customers based on their servicing deadline and constraints, benefiting both D-RES owners and customers in terms of providing economic revenue and reducing the cost of supplied energy. In this context, this paper proposes a dynamic matching framework using model predictive control (MPC) to enable local energy sharing in power system operation. The proposed matching framework matches flexible customers with D-RES to maximize social welfare in the matching market, while meeting the customers' servicing constraints prior to their deadline. Simulations are conducted on a test power system using multiple matching algorithms across different load and generation scenarios and the results highlighted the efficiency of proposed framework in matching flexible customers with the appropriate supply sources to maximize social welfare in the matching market.**

***Index Terms*—Dynamic Matching, social welfare, model predictive control (MPC), flexible customer, distributed renewable energy sources (D-RES).**

I. Introduction

Driven by the integration of distributed energy resources (DERs) and the recent advances in communication infrastructures, power system is rapidly transforming from a centralized structure to a decentralized model [1]. In a centralized power system, power generation is dependent on large-scale generation units, while in a decentralized system, distributed renewable energy sources (D-RES) are the main sources of power supply [2]. Integration of D-RES and flexible resources in decentralized power system enables communities to locally supply their energy requirements, while introducing a variety of financial revenue streams and cost-saving opportunities to their operation [3], [4]. These outcomes are achievable with coordinated operation of D-RES and flexible resources [5]. Therefore, the most beneficial way of coordinating D-RES and flexible resources needs to be investigated to address the energy requirements in local communities, while offering them a variate of cost-savings opportunities.

A. Technical Literature

Recent studies revealed the advantages of integrating DERs to introduce distributed energy services and leverage power system operation [6]–[11]. However, provision of energy services by these resources relies on the implementation of appropriate coordination schemes. In this regard, multiple solutions are proposed to integrate DERs and coordinate their operation in power system [12]. One of these solutions is developing peer-to-peer (P2P) energy trading that seeks to enable residential prosumers-customers with small-scale DERs to locally trade energy and supply their energy requirements [13]. P2P energy trading concept is comprehensively studied and the active elements in P2P markets are fully discovered in [14], [15]. The main components of a P2P energy market are physical and virtual infrastructures, as well as the participants seeking to trade energy services. To enable energy trading between the participants, local market designs need to be developed and the role of different authorities and the challenges associated with trading energy within the existing physical infrastructure need be taken into account [16], [17].

Recently, great efforts are made to develop P2P energy trading based on matching concept in power system. In [18], an online matching model is proposed for flexible customers and DERs in smart grids, where the key role of demand flexibility in reducing customers' payment is highlighted. The authors in [19] developed an online matching model to match the flexible customers with D-RES, respecting the randomness in load request and D-RES generation availability. A P2P energy trading framework is presented in [20], where a trading matrix formed by an iterative-based methodology is implemented to match the energy seller and buyer. In [21], model predictive control (MPC) is implemented for minimizing customers' dissatisfaction and generation cost in multiple renewable-based microgrid systems, connected to locally trade energy. A similar energy trading model is studied with MPC considering controllable loads in [22].

Considering the recent advances in forecasting methodologies, future realizations for customers' load request and D-RES availability can be provided to make the decision-making process much more efficient in the matching markets. The proposed matching algorithms in [19] only utilize current data and future realizations of load request and D-RES generation are not taken into account for dynamic matching. The proposed model in [21] only enables local energy sharing between the microgrids and doesn't consider any flexibility in customers' load request. Moreover, although the proposed model in [22] considers controllable loads, it neglects the criticality feature for the considered customers, effecting the level of offered flexibility.

B. Contributions and Paper Structure

This paper proposes a dynamic matching framework with MPC to match D-RES with flexible customers based on their servicing constraints, i.e., load request, deadline and criticality. MPC utilizes the most recent forecasts for D-RES generation and customers' load request to optimize the matching decisions in specific controlling horizons, where the matching decisions for the first instant are implemented as the solution to the matching market. This solution considers customers' flexibility, as well as the rate of D-RES utilization for dynamic matching to maximize social welfare in the matching market. A novel queuing system is developed to model the customers' flexibility, while ensuring that the submitted load requests are served prior to customers' deadline. Simulations are conducted on a test power system using multiple matching algorithms across different load and generation scenarios and comparison results are provided to validate the efficiency of proposed framework in matching D-RES with flexible customers.

The rest of the paper is organized as follows: The structure of proposed dynamic matching framework along with problem formulation is presented in section II. Numerical results are presented and discussed in Section III and the paper is concluded in Section IV.

II. Dynamic Matching Framework

In this section, the structure of proposed dynamic matching framework, supply and load models, as well as MPC implementation are first described and then the studied dynamic matching problem is formulated. The structure of proposed dynamic matching framework is illustrated in Fig. 1.

In Fig. 1, forecasts for D-RES generation, customers' load request and their respective servicing constraints are given to the MPC. Considering the received forecasts and real-time load and generation data, MPC runs an optimization problem for multiple control horizons, i.e., t_1-t_3, t_2-t_4, t_3-t_5 and finds the matching solutions for every horizon. The results for the first instant in every control horizon determine the optimal solutions for the matching problem that maximize social welfare in the matching market. For instance, based on

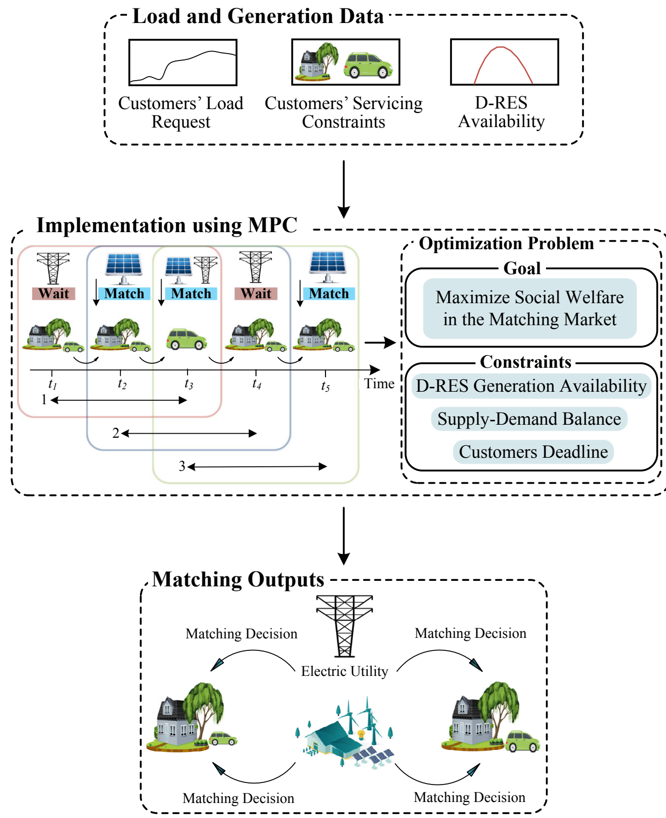

Fig. 1. Matching market structure with model predictive control.

the described procedure, at time t_1, when a flexible customer arrives at the market and D-RES generation is not available, MPC lets the customer to stay in the market until t_2, where D-RES generation becomes available. At this time, MPC matches the flexible customer to the D-RES and supplies the load request, respecting the deadline and criticality of customer. It is noteworthy that whenever D-RES generation is not sufficient to supply the load request of a critical customer, e.g., t_3, power grid supplies the remaining load request.

A. Supply Model

The supply sources in the proposed matching framework are D-RES generation and grid power. D-RES generation and grid power at time t are respectively denoted by r_t and p_t, where $t \in T$. Power generation of D-RES, such as photovoltaic (PV) and wind systems, is dependent on many factors, i.e., solar irradiation and wind speed, etc. Therefore, the availability of D-RES generation to supply load requests is not guaranteed, while the grid power is assumed to be large enough to serve critical customers at any given time in the market. Note that the generation cost of r_t is zero, while p_t is priced at electricity tariff in power distribution system, c/kWh.

B. Load Model

In the proposed matching framework, customer i arrives at time a^i and submits its load request, deadline d^i and criticality measure b^i, which expresses the rate according to which its willingness to pay decreases over time, from a^i until d^i. Considering these features, the non-negative utility function for the customer i representing its willingness to pay can be expressed as:

$$\pi_t^i = c - b^i(t - a^i), \quad a^i \leq t \leq d^i, \tag{1}$$

$$b^i = \varphi c/(d^i - a^i), \tag{2}$$

where $\varphi \in [0, 1]$ determines the reduction rate in customer's willingness to pay for a unit of energy. To model the customers' flexibility, a queuing system is implemented that captures the offered flexibility by customers in the market, concerning their arrival, deadline and criticality. The implemented queuing system enforces a deadline-based policy to ensure that customers' servicing constraints are satisfied prior to their deadline. Further details regarding the implementation of queuing system to model the customers' flexibility can be found in [23].

C. Implementation using Model Predictive Control

The MPC integrated in the proposed matching framework considers the future realizations of D-RES generation, customers' load request, their flexibility and deadline to decide upon matching the active flexible customers with appropriate supply sources. MPC implements a control horizon that can vary based on the extents of forecast availability for future data. Fig. 2 represents three consecutive control horizons T_1, T_2 and T_3 that start at t_1, t_2 and t_3 and end at $t_1 + T_1$, $t_2 + T_2$ and $t_3 + T_3$, respectively.

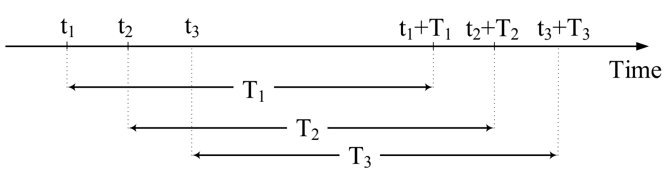

Fig. 2. Timeline for the integrated MPC.

When the matching problem is solved for every control horizon, the results for the first instant in every control horizon are taken as the solutions to the dynamic matching problem. This process is repeated until the matching problem is solved for the last control horizon. In this way, matching decisions are achieved respecting the actual load and generation data as well as future forecasts for the load request and D-RES generation.

D. Dynamic Matching Problem Formulation

Let denote the active customers in the matching market at time t by A_t, and the set of supply types at time t by S_t, where $S_t = \{ps, rs\}$. Denoting the unsupplied load request by q_t^i, the amount of supply of type j matched to the customer i at time t can be denoted by $M_t(j, i)$. Hence, the matching problem can be formulated as follows:

$$\max_{M_t} \sum_{t \in T} \sum_{i \in A_t} \sum_{j \in S_t} (\pi_t^i - c_j) M_t(j, i), \tag{3}$$

s.t.

$$\sum_{j \in S_t} M_t(j, i) \leq q_t^i, \ \forall i, t < d^i, \tag{4}$$

$$\sum_{j \in S_t} M_t(j, i) = q_t^i, \ \forall i, t = d^i, \tag{5}$$

$$\sum_{i \in A_t} M_t(\mathrm{rs}, i) \leq r_t, \ \forall t. \tag{6}$$

The objective function expressed in (3) maximizes the social welfare gained from matching supply j to the customer i. Flexible customers are supplied according to the matching decisions in (4) and any critical customer with an immediate deadline is ensured to be served in (5). Finally, the local renewable supply is limited to its available capacity in (6).

III. Numerical Study

In this section, simulations are conducted on a test power system using multiple matching algorithms across different load and generation scenarios and the associate numerical results are presented and discussed.

A. Simulation Setup

To evaluate the performance of the proposed MPC for dynamic matching in power system, three other matching algorithms are considered in this study. The first algorithm is matching upon arrival (MA) that matches the customers with available D-RES generation or grid power upon their arrival. The second algorithm is matching to the highest (MH) that lets the flexible customers stay in the market until sufficient D-RES generation becomes available to serve them. In case D-RES generation is insufficient, any remaining critical customer with an immediate deadline is matched to the grid. The third algorithm is matching to earliest deadline (MED) that matches the customers with the earliest deadline to the available D-RES generation. Similar to the MH, in case local supply is insufficient, any remaining critical customer with an immediate deadline is matched to the grid.

Simulations are conducted across four different scenarios for D-RES generation, as well as customers' load request and servicing constraints. In scenario 1, limited D-RES generation is available during the middle of the day and flexible customers are characterized by random short deadlines, with an average of 4 time periods from the arrival. The average load and generation profiles for this scenarios are shown in Fig. 3-(a). In scenario 2, D-RES generation exceeds load request during the middle of the day. In this scenario, flexible customers that arrive earlier into the market are characterized by larger deadlines, while the others arriving during the middle of the day have shorter deadlines. The average load and generation profiles for this scenarios are shown in Fig. 3-(b). In scenario 3, sufficient D-RES generation is available during the middle of the day and flexible customers characterized by random large deadlines, with an average of 8 time periods from the arrival are considered. The average load and generation profiles for this scenarios are shown in Fig. 3-(c). Scenario 4 considers customers characterized by fixed large deadlines of 8 time periods from the arrival. The average load and generation profiles for this scenarios are shown in Fig. 3-(d).

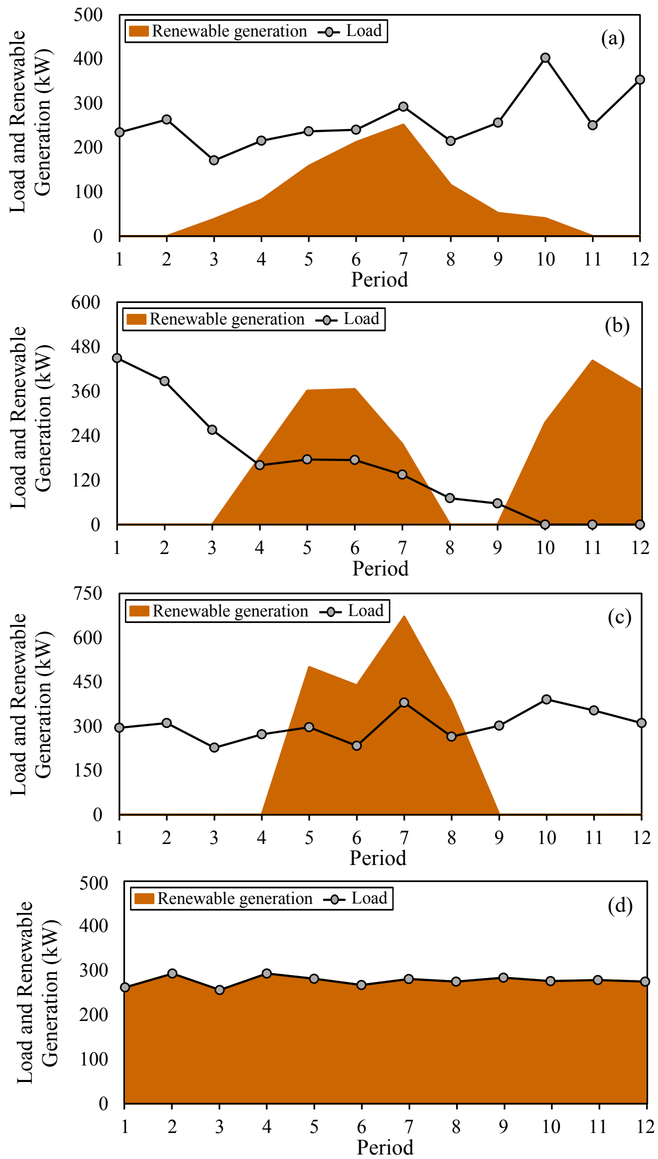

Fig. 3. Average load request and renewable generation in the matching market: (a) Scenario 1, (b) Scenario 2, (c) Scenario 3, (d) Scenario 4.

To conduct the simulations, load request and D-RES generation data are generated for 800 epochs using normal distribution with the average values shown in Fig. 3, where every epoch includes a 12-period load request and a 12-period generation profile. The standard deviation to produce load and local generation data is assumed to be 15% of the average load and generation for scenarios 1-3 and to consider severe uncertainty in the load request and generation profiles, it is assumed to be 50% of the average load and generation for scenario 4. We developed our proposed MPC with 12 runs, where every run considers a 8-period control horizon. Therefor, the total number of runs to solve the matching problem is $(800 \text{ epochs}) \times (12 \text{ runs}) = 9600$. The studied matching problem is modeled as a mixed-integer linear programming (MILP) problem and solved using General Algebraic Modeling System (GAMS) package on a desktop computer with a 4.0-GHz i7 processor and 32 GB of RAM.

B. Numerical Results

The average social welfare achieved by MPC and other matching algorithms for scenarios 1-4 is summarized in Table I. According to the results in Table I, MPC achieves the highest social welfare for every scenario among the matching algorithms. The results show that MPC is efficient in capturing customers' flexibility and local generation availability to make appropriate matching strategies in a variety of scenarios, thus maximizing social welfare in the matching market. Further details regrading the performance of matching algorithms in every scenario are discussed next.

TABLE I
AVERAGE SOCIAL WELFARE IN THE MATCHING MARKET

Scenario/Algorithm	MA	MH	MED	MPC
Scenario 1 ($)	150.4	43	28.4	150.4
Scenario 2 ($)	84.7	136.7	118.6	149.6
Scenario 3 ($)	160	178.7	174.3	256
Scenario 4 ($)	232.7	262.2	260.2	313.2
Average, all ($)	156.9	155.15	145.3	217.3

C. Discussions

In this section, simulation results for representative epochs with the load and local generation data expressed in Fig. 3 are discussed. The matching results achieved by the algorithms MA, MH and MPC for a representative epoch in scenario 1 are shown in Fig. 4. In Fig. 4, it is shown that the best matching strategy is to supply customers upon their arrival, which is taken by MA and MPC, as shown in Figs. 4-(a) and 4-(c). In this scenario, the flexibility to be offered by customers is limited and local generation is not sufficient to supply all the load requests. As shown in Fig. 4-(b), MH algorithm allows the customers to wait in the market, but since there is no sufficient local generation available, grid power supplies the remaining load requests, leading to a lower social welfare (see Table I).

The matching results achieved by the algorithms MA, MH and MPC for a representative epoch in scenario 2 are shown in Fig. 5. According to the results in Fig. 5-(a), MA algorithm fails to capture the customers' flexibility to match them to the excess local generation during the middle of the epoch. On the other side, in Fig. 5-(b), MH algorithm allows all the customers arriving earlier to wait until local generation becomes available during the middle of the epoch. However, since the customers arriving later at the market are characterized by higher criticality rates, most of their load request is supplied by the grid power. Therefore, as expressed in Table I, the best matching strategy is neither to let the customers arriving earlier wait in

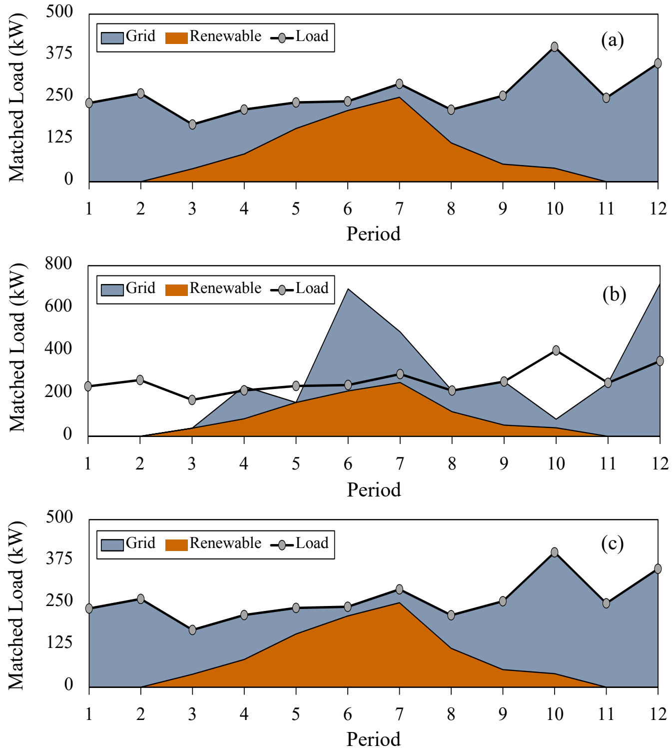

Fig. 4. Matching on a representative epoch (Scenario 1): (a) MA algorithm, (b) MH algorithm, (c) MPC.

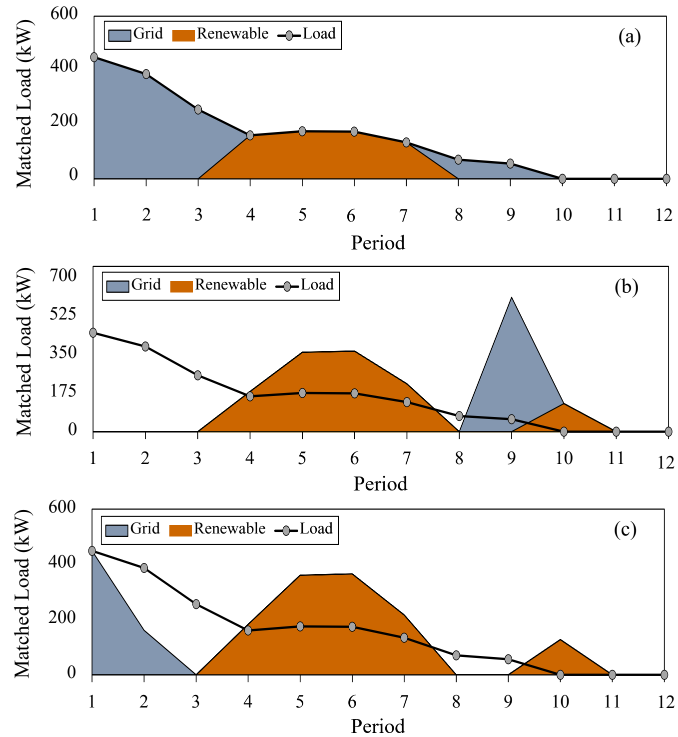

Fig. 5. Matching on a representative epoch (Scenario 2): (a) MA algorithm, (b) MH algorithm, (c) MPC.

the market nor to match them upon their arrival. In fact, the best strategy in this scenario is to match the customers with higher criticality rates to the grid power and let the others with lower criticality rates to wait in the market and get matched to the local generation that becomes available in larger scales during the middle of the epoch. In this case, no customer with an increasing criticality would remain unmatched to be supplied by the grid power, as shown in Fig. 5-(c).

The matching results achieved by the algorithms MA, MED and MPC for a representative epoch in scenario 3 are shown in Fig. 6. As shown in Fig. 6-(a), by implementing MA algorithm, all the customers are served upon their arrival and therefore excess local generation during the middle of the epoch is not efficiently utilized. In Fig. 6-(b), MED algorithm allows the customers arriving earlier to wait until their deadline, hoping to match them to the local generation. As shown, this strategy leads to an aggregated load request at the end of the epoch, which is served by the grid power. In this scenario, the most optimal matching strategy taken by the MPC is to efficiently let the non-critical customers wait in the market and match them to the local generation, while matching the critical ones upon their arrival, as shown in Fig. 6-(c).

In scenario 4, severe uncertainty is considered for local generation as well as the customers' load request and their respective deadline and criticality. According to the results, MPC achieves the highest social welfare, \$313.2, while the algorithms MH, MED and MA respectively achieve \$262.2, \$260.2 and \$232.7. These results are similar to the outcomes of matching market in scenarios 2 and 3, where the best strategy is to match the critical customers upon their arrival, while letting the non-critical ones to wait in the market and get matched to the D-RES, respecting the local generation availability.

In summary, the matching results for scenarios 1-4 revealed that taking a fixed matching strategy to match the customers with local generation doesn't guarantee the most desired outcome for the matching market. It was found that in order to archive the most desired social welfare in the matching market, it is crucial to make a balance between the two strategies, waiting to match to the highest and matching upon arrival. The results showed that MPC efficiently leverages the flexibility of customers with lower criticality rates to match them to the excess local generation and meanwhile match the customers with higher criticality rates to the grid power upon their arrival, which avoids loss of social welfare in the matching market.

IV. Conclusions

In this paper, an optimization framework based on MPC is proposed for dynamic matching in power systems integrated with flexible customers and D-RES. The proposed MPC considers the forecasts for D-RES generation and matches the flexible customers with the most appropriate supply, concerning their servicing constraints, i.e., deadline and criticality. The goal of proposed framework is to maximize social welfare in the matching market, respecting the customers' servicing constraints and D-RES generation availability. Simulations are

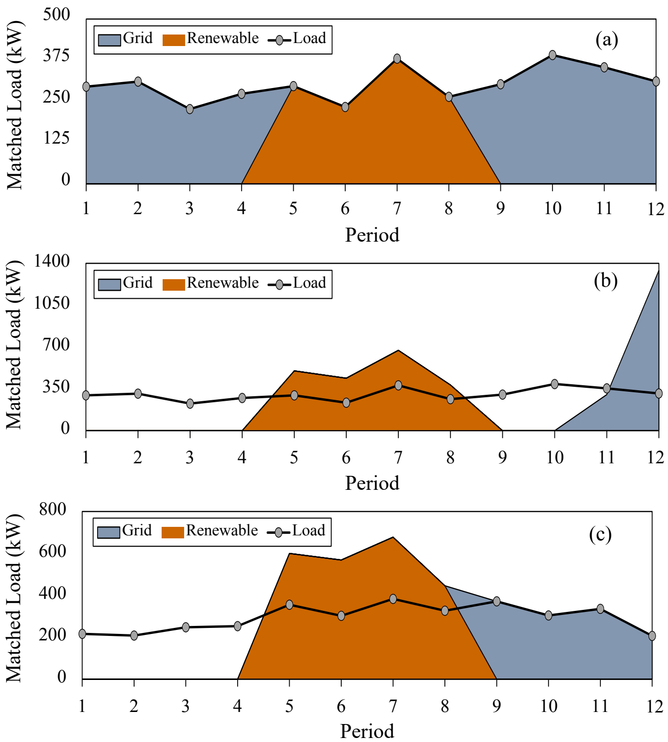

Fig. 6. Matching on a representative epoch (Scenario 3): (a) MA algorithm, (b) MED algorithm, (c) MPC.

conducted on a test power system across multiple scenarios for D-RES generation and customers' load request. The results highlighted the efficiency of MPC in making appropriate matching decisions for every scenario in the market, while ensuring that customers are served prior to their deadline. In particular, the results showed that MPC is able to make a balance between matching critical customers upon their arrival and letting the non-critical customers to wait and get matched to the D-RES generation, which avoids the loss of social welfare in the matching market.

For future works, the proposed matching framework can be extended to include storage devices in the matching market, which can enable D-RES owners to manage the uncertainty in their local generation. Implementing the proposed framework in power distribution system with considering network constraints is also in order.

References

[1] M. K. AlAshery, Z. Yi, D. Shi, X. Lu, C. Xu, Z. Wang, and W. Qiao, "A blockchain-enabled multi-settlement quasi-ideal peer-to-peer trading framework," *IEEE Transactions on Smart Grid*, vol. 12, no. 1, pp. 885–896, 2020.

[2] M. Parvania, M. Fotuhi-Firuzabad, and M. Shahidehpour, "Comparative hourly scheduling of centralized and distributed storage in day-ahead markets," *IEEE Transactions on Sustainable Energy*, vol. 5, no. 3, pp. 729–737, 2014.

[3] J. Guerrero, A. C. Chapman, and G. Verbič, "Decentralized p2p energy trading under network constraints in a low-voltage network," *IEEE Transactions on Smart Grid*, vol. 10, no. 5, pp. 5163–5173, 2018.

[4] B. Vand, R. Ruusu, A. Hasan, and B. M. Delgado, "Optimal management of energy sharing in a community of buildings using a model predictive control," *Energy Conversion and Management*, vol. 239, p. 114178, 2021.

[5] M. Hu, F. Xiao, and S. Wang, "Neighborhood-level coordination and negotiation techniques for managing demand-side flexibility in residential microgrids," *Renewable and Sustainable Energy Reviews*, vol. 135, p. 110248, 2021.

[6] R. Khatami, M. Parvania, and K. Oikonomou, "Continuous-time optimal charging control of plug-in electric vehicles," in *2018 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT)*. IEEE, 2018, pp. 1–5.

[7] K. Oikonomou, M. Parvania, and R. Khatami, "Deliverable energy flexibility scheduling for active distribution networks," *IEEE Transactions on Smart Grid*, vol. 11, no. 1, pp. 655–664, 2019.

[8] ——, "Coordinated deliverable energy flexibility and regulation capacity of distribution networks," *International Journal of Electrical Power & Energy Systems*, vol. 123, p. 106219, 2020.

[9] R. Khatami, M. Heidarifar, M. Parvania, and P. Khargonekar, "Scheduling and pricing of load flexibility in power systems," *IEEE Journal of Selected Topics in Signal Processing*, vol. 12, no. 4, pp. 645–656, 2018.

[10] R. Dzikowski, "Dso–tso coordination of day-ahead operation planning with the use of distributed energy resources," *Energies*, vol. 13, no. 14, p. 3559, 2020.

[11] X. Yang, C. Xu, H. He, W. Yao, J. Wen, and Y. Zhang, "Flexibility provisions in active distribution networks with uncertainties," *IEEE Transactions on Sustainable Energy*, vol. 12, no. 1, pp. 553–567, 2020.

[12] J. Guerrero, D. Gebbran, S. Mhanna, A. C. Chapman, and G. Verbič, "Towards a transactive energy system for integration of distributed energy resources: Home energy management, distributed optimal power flow, and peer-to-peer energy trading," *Renewable and Sustainable Energy Reviews*, vol. 132, p. 110000, 2020.

[13] O. Abrishambaf, F. Lezama, P. Faria, and Z. Vale, "Towards transactive energy systems: An analysis on current trends," *Energy Strategy Reviews*, vol. 26, p. 100418, 2019.

[14] T. Sousa, T. Soares, P. Pinson, F. Moret, T. Baroche, and E. Sorin, "Peer-to-peer and community-based markets: A comprehensive review," *Renewable and Sustainable Energy Reviews*, vol. 104, pp. 367–378, 2019.

[15] W. Tushar, C. Yuen, T. K. Saha, T. Morstyn, A. C. Chapman, M. J. E. Alam, S. Hanif, and H. V. Poor, "Peer-to-peer energy systems for connected communities: A review of recent advances and emerging challenges," *Applied Energy*, vol. 282, p. 116131, 2021.

[16] Y. Parag and B. K. Sovacool, "Electricity market design for the prosumer era," *Nature energy*, vol. 1, no. 4, pp. 1–6, 2016.

[17] S. Bjarghov, M. Löschenbrand, A. I. Saif, R. A. Pedrero, C. Pfeiffer, S. K. Khadem, M. Rabelhofer, F. Revheim, and H. Farahmand, "Developments and challenges in local electricity markets: A comprehensive review," *IEEE Access*, vol. 9, pp. 58 910–58 943, 2021.

[18] P. Ströhle and C. M. Flath, "Local matching of flexible load in smart grids," *European Journal of Operational Research*, vol. 253, no. 3, pp. 811–824, 2016.

[19] D. Muthirayan, M. Parvania, and P. P. Khargonekar, "Online algorithms for dynamic matching markets in power distribution systems," *IEEE Control Systems Letters*, vol. 5, no. 3, pp. 995–1000, 2020.

[20] L. Chen, N. Liu, C. Li, S. Zhang, and X. Yan, "Peer-to-peer energy sharing with dynamic network structures," *Applied Energy*, vol. 291, p. 116831, 2021.

[21] Y. Du, J. Wu, S. Li, C. Long, and I. C. Paschalidis, "Distributed mpc for coordinated energy efficiency utilization in microgrid systems," *IEEE Transactions on Smart Grid*, vol. 10, no. 2, pp. 1781–1790, 2017.

[22] Y. Du, J. Wu, S. Li, C. Long, and S. Onori, "Coordinated energy dispatch of autonomous microgrids with distributed mpc optimization," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 9, pp. 5289–5298, 2019.

[23] R. Khatami, M. Parvania, and A. Bagherinezhad, "Continuous-time model predictive control for real-time flexibility scheduling of plugin electric vehicles," *IFAC-PapersOnLine*, vol. 51, no. 28, pp. 498–503, 2018.